THREE ESSAYS ON CAPITAL MARKETS

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Kai Wu
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THREE ESSAYS ON CAPITAL MARKETS

Kai Wu, Ph.D.

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This dissertation is a combination of three papers on capital markets.

The first chapter studies on the impact of cost of capital on corporate investment and financing decisions. Previous literature shows that the implied cost of capital (ICC) has a negative effect on investment, while the factor model-based estimates have positive effects on investment. Our paper documents that these alternative cost-of-equity proxies also have opposite effects on equity issuance. We show that the ICC has negative effects on investment and equity issuance by capturing the firm-specific discount rate news, whereas the factor model-based estimates have positive effects on these decisions by capturing the market-wide cash flow news. Thus, the opposite effects of the ICC and factor-model based estimates can be explained by their distinctive information contents.

In the second chapter, I evaluate the economic consequences of advisory misconduct by estimating the effect of publicly disclosed regulatory actions of mutual fund advisors on fund flows. Based on a broad set of misconduct events from 2000-2013, I find a 5% reduction in fund flows to malfeasant advisors in one year following the misconduct. Further analysis using the 2001 SEC electronic filing mandate as a positive shock to misconduct transparency corroborates these results. In order to mitigate the negative impact on flows, mutual fund companies tend to raise marketing expenditures, reduce contractual incentives and relax investment restrictions in subsequent years. Moreover, advisory misconduct adversely affects advising relationships and advisor survival. My

findings highlight the significant impact of misconduct on fund flows and advisory contracting in the mutual fund industry.

In the last chapter, we evaluate the effectiveness of Interfund Lending Programs for both borrowing and lending funds in fund families. We find strong support for the positive effect for borrowing funds. Under extreme distress ILP-funds have 0.32% higher returns than non-ILP funds in the following week. Sub-sample analysis shows that the positive effect is mainly driven by equity and municipal funds, and the effect is more pronounced when funds hold illiquid assets, when external funding cost is high, and when fund families are more diversified in styles. Moreover, Interfund Lending Programs facilitate liquidity management and reduce external borrowing activities. But we find limited evidence concerning the effectiveness for lending funds. Taken together, our results suggest that Interfund Lending Programs play a crucial part as internal capital market in fund families.

BIOGRAPHICAL SKETCH

Kai Wu was a Ph.D. student at the Dyson School of Applied Economics and Management, Cornell University from 2013-2018. He defended this dissertation in April 2018, and then became a faculty member at the Central University of Finance and Economics, Beijing, China.

Prior to entering Cornell for his Ph.D. degree, he graduated from Harbin Engineering University in 2010, with a bachelor degree in Management. During 2010-2013 he was a student at Wang Yanan Institute of Studies in Economics, Xiamen University.

TO MY PARENTS

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CHAPTER 1

UNDERSTANDING THE EFFECTS OF ALTERNATIVE COST-OF-EQUITY PROXIES ON CORPORATE INVESTMENT AND FINANCING

The CAPM and the (Fama and French, 1992, 1993) model (FFM) are currently the standard textbook choices for estimating the cost of equity. Yet, there is mounting skepticism over their application for capital budgeting decisions from both academic researchers and practitioners. For instance, Levi and Welch (2014) contend that factor model-based estimates are useless for capital budgeting purposes as they predict subsequent returns with a wrong sign. Hackel (2011) also raises doubt about using factor models in estimating the cost of equity.

Recent literature suggests the implied cost of capital (ICC) as an alternative way of estimating the cost of equity, by equating the stock price to the present value of expected future cash flows.[1] Frank and Shen (2016) document that the ICC has the anticipated *negative* effect on investment. They also show, however, that the factor model-based estimates have *positive* effects on investment. Our paper contributes to understanding the puzzling opposite effects of alternative cost-of-equity proxies on investment by investigating the nature of their information contents.

[1]The ICC has been used in various contexts, especially in asset pricing. For example, previous papers use the ICC to study: the unconditional equity premium (Claus and Thomas (2001) and Fama and French (2002)); stock market return predictability (Li et al. (2013)); theories on betas (Kaplan and Ruback (1995), Botosan (1997), Gebhardt et al. (2001), Gode and Mohanram (2003), Brav et al. (2005), and Easton and Monahan (2005)); international asset pricing (Lee et al. (2009)); default risk (Chava and Purnanandam (2010)); cross-sectional expected returns (Hou and Van Dijk (2010), Botosan et al. (2011)); stock return volatility (Friend et al. (1978)); and the cost of equity (Burgstahler et al. (2006), Botosan and Plumlee (2005), and Hughes et al. (2009)).

According to Abel and Blanchard (1986), investment is affected negatively by discount rates and positively by expected cash flows. In particular, they show that the discount rate and the marginal profit components of Tobin's q have significant and opposite effects on investment beyond q. Accordingly, if the discount rate drives the stock return, the expected stock return will show a negative effect on investment because an increase in the discount rate implies higher expected return (Campbell et al. (2010)) and low investment (Abel and Blanchard (1986)). When the stock return is driven by cash flow growth, however, the expected stock return will have a positive effect on investment (Fama (1990) and Schwert (1990)). Thus, whether the ICC and factor model-based estimates capture the shocks to expected cash flows or discount rates is critical in understanding their opposite effects on corporate investment.

The ICC is designed to capture the firm-specific discount rate as demonstrated in Pastor et al. (2008) and Chen et al. (2013). Factor model-based estimates, however, may be related more to cash flows and market-wide information. For instance, Vuolteenaho (2002) find that firm-level stock returns are mainly driven by cash flow news rather than by discount rate news. Campbell and Vuolteenaho (2004) find that the required return on a stock is determined by permanent cash flow shocks to the market and the temporary shocks to the market discount rate. Chen et al. (2013) show that the common variation in stock returns is driven more by cash flow news than discount rate news. Moreover, Campbell et al. (2010) suggest that the systematic risks of value and growth stocks are determined by the properties of their cash flow fundamentals. Patton and Verardo (2012) also suggest that betas reflect the revised expectations about the profitability of the aggregate economy. These studies imply that factor model-based estimates may capture more of cash flow news that are related to the aggregate economy or market-wide shocks.

Given the current state of the literature on the cost of equity, the focus of our investigation is twofold: 1) whether the cash flow or discount rate news is reflected on the cost-of-equity proxies and corporate investment; and 2) whether private or market-wide information drives the link between the cost-of-equity proxies and corporate investment. To this end, we also explore the equity financing channel because Morck et al. (1990) and Baker et al. (2003) suggest that the key channel for the cost of equity to affect corporate investment is through the issuance of new equity. Given that the cost of equity is a critical input from the stock market in the capital budgeting process, the equity financing channel may help us better understand the information contents of cost-of-equity proxies, particularly in the presence of asymmetric information. Moreover, the link between cost-of-equity proxies and equity issuance has not yet been explored.

Following Chen et al. (2013) and Campbell and Shiller (1988), we decompose realized stock returns into two components; discount rate news and cash flow news. We confirm that cash flow news has positive effects, while discount rate news has negative effects, on investment and equity issuance decisions. We then show that ICC measures are associated positively with discount rate news and negatively with cash flow news, whereas factor model-based estimates are associated negatively with discount rate news and positively with cash flow news. Furthermore, using the Campbell and Vuolteenaho (2004) two-beta model and similar decomposition of other factors, we find that corporate investment and equity issuance decisions are mainly driven by the bad beta which reflects news about market-wide cash flows. These results suggest that the positive effects of the factor model-based estimates on investment and equity issuance come mainly from market-wide cash flow news. Thus, the opposite effects of the ICC and factor model-based estimates on investment and financing decisions can be attributed to the ways they reflect cash flow news and discount rate news.

To further understand the link between the cost-of-equity proxies and discount rate news/cash flow news in more controlled settings, we also examine their behavior around recessions and following exogenous shocks. The recession periods are characterized by the heightened uncertainty and risk aversion of investors with diminishing cash flows (González-Hermosillo (2008), Coudert and Gex (2008), and Frank and Goyal (2009)), which implies positive discount rate shocks and negative cash flow shocks. Our results show that, prior to recessions, ICC measures steeply increase, reflecting mainly positive discount rate shocks, whereas factor model-based estimates exhibit steep decreases, reflecting mainly negative cash flow shocks. These results suggest that the ICC captures mainly the discount rate news, while factor model-based estimates capture the cash flow news.

We also utilize Taxpayer Relief Act of 1997 and the Jobs and Growth Tax Relief Reconciliation Act of 2003 as exogenous shocks to the discount rate. Dhaliwal et al. (2007) and Dai et al. (2013) show that these legislations have reduced the cost of equity for financially constrained firms. We find that, following these legislations, ICC measures decrease, while factor model-based estimates increase, especially for financially constrained firms whose investment and financing decisions are most likely to be sensitive to the discount rate shock. Again, these findings indicate that the ICC captures mainly the discount rate shock, while factor model-based estimates capture the cash flow effect of the discount rate shocks.

The effect of the cost of equity on investment through the external financing channel is expected to be more pronounced for firms with greater financial constraint/equity dependence (Baker et al. (2003)). Accordingly, we examine the effects of the cost-of-equity proxies on net equity issuance as well as investment, conditional on firm's equity dependence. We find that the ICC has significant and negative effects on equity issuance and investment for equity-dependent firms. The factor model-based estimates do not show significant effects on these decisions for equity-dependent firms. Instead, they show positive effects on investment and equity issuance for less equity-dependent firms. These results suggest that the ICC, reflecting mainly the firm-specific discount rate news, has significant effects on investment and financing decisions, for firms that are more likely to be sensitive to the discount rate news. In contrast, the factor model-based estimates appear to predict investment and financing decisions positively for less equity-dependent firms by reflecting fundamentals affecting cash flows. These results suggest that the ICC and factor-model based estimates may also differ in another dimension: whether they reflect the private or public information.

Chen et al. (2007) suggest that investment decisions respond to stock prices as firms are informed about their investments from the stock market. The main driver of such an information feedback channel is private information which is the component of stock return that is not explained by the market and industry portfolio. Consequently, we test whether the effects of the ICC and factor model-based estimates on investment and financing decisions are through the private or public information channel. Our findings show that the ICC has significant and negative effects on investment and equity issuance for firms with greater private information, whereas factor model-based estimates show significant and positive effects for firms with less private information.

We further examine the effects of the ICC and factor model-based estimates on investment including M&As (and R&D), because previous studies suggest that these investments are particularly affected by private information on s-tock valuation.[2] We find that the ICC has significant and negative effects on this broadly defined investment, whereas factor model-based estimates show insignificant effects. These findings suggest that firms' investment decisions are particularly sensitive to private information on the discount rate. We further address errors-in-variable issues regarding q and cost-of-equity proxies, utilize fundamentals-based q, control for other firm characteristics, and consider alternative specifications. Our results remain robust.

Taken together, our results suggest that the opposite effects of the ICC and factor model-based estimates on corporate investment and financing decisions can be explained by their distinct information contents. The ICC has negative effects on investment and financing decisions as it contains information about the firm-specific discount rate. Its main effects are found for firms with more equity dependence and more private information whose decisions are likely to be most sensitive to the discount rate news. In contrast, factor model-based estimates contain information about market-wide cash flows and have positive effects on investment and equity issuance for firms with less equity dependence and less private information.

Our findings have important implications for finance instructors and researchers. We teach students that capital budgeting decisions involve estimating cash flows from a project, and then applying the cost of capital from capital

[2]For example, see Shleifer and Vishny (2003), Rhodes-Kropf and Viswanathan (2004), Rhodes-Kropf et al. (2005), Dong et al. (2006), and Brown et al. (2009).

markets as the discount rate or the hurdle rate. Our results suggest that the ICC is close to the effective cost of equity managers come up with after considering the market conditions and expected cash flows. In contrast, factor model-based estimates contain information about market-wide expected cash flows. In this regard, factor models miss out some important information on the discount rate, especially for firms whose investment and financing decisions are most sensitive to it.

Our paper is related to the literature on estimating the cost of equity. The cost of equity is indispensable for capital budgeting but the current practice of estimating it remains controversial. Levi and Welch (2017) maintain that factor models fail because they are based on common inputs for factor exposures estimated from historical observations.[3] Our results suggest that factor models do not capture the firm-specific discount rate but market-wide cash flow information. Frank and Shen (2016) argue that both the ICC and factor-model-based estimates, despite their opposite effects, provide relevant and independent information for corporate investment. However, they remain agnostic as to the information contents of these cost-of-equity proxies. Our study contributes to the literature by showing the nature of information conveyed by these alternative proxies and by explaining their opposite effects. Levi and Welch (2017) argue that one obstacle to abandoning factor models may be the absence of an alternative. We suggest that the ICC could be a practical alternative to factor models.

Our paper also contributes to the literature on the relation between factor model-based and survey-based expected returns. Greenwood and Shleifer (2014) document that factor model-based estimates and the surveyed expect-

[3]They suggest that incorporating forward-looking betas may improve factor models.

ed returns are negatively correlated with each other. Moreover, they show that the survey expectations are more consistent with investors' actual behavior like mutual fund inflows. Gennaioli et al. (2016) further show that the survey expectation of earnings also affects corporate investment. Consistent with these findings, our results suggest that the ICC, reflecting the forward-looking discount rate based on the analysts-surveyed expected cash flows, negatively affect corporate investment and financing decisions, while factor model-based estimates show opposite effects.

Our study is also linked to the q-model theory with the interdependence of investment and financing decisions (for example, Gomes (2001) and Bolton et al. (2011)). This theory suggests that external financing costs due to asymmetric information and managerial incentive problems have impact on investment beyond q. Consistent with the theory, our findings suggest that the ICC is highly informative beyond q, particularly about the risk of investment opportunities.

We also contribute to the literature on private information in stock price for investment decisions. For example, previous studies conjecture that the stock market affects corporate investment as it informs managers about real variables (Dow and Gorton (1997), Subrahmanyam and Titman (1999), Dow and Rahi (2003), Chen et al. (2007), and Goldstein and Guembel (2008)).[4] Our findings suggest that the discount rate implied by the stock price is particularly important information for managers to assess investment and financing decisions. By capturing the firm-specific discount rate, the ICC informs managers about the market's assessment of the firm's project risk, which they incorporate in their investment and financing decisions.

[4] Bond and Goldstein (2011) provides an excellent review on the real effects of financial markets and their implications.

1.1 Data and Methodology

1.1.1 Sample Construction

Our initial sample consists of US firms from the Center for Research in Security Prices (CRSP)/ Compustat Merged Database from 1985 to 2013. We obtain the stock price, the number of shares outstanding, the SIC code, monthly returns from CRSP, firm-level annual accounting data from Compustat, analysts' earnings forecasts from I/B/E/S, and the nominal GDP growth rates from the Bureau of Economic Analysis. We exclude firms operating in regulated utilities (SIC code 4000-4999) and financial industries (SIC code 6000-6999). We further drop firm-year observations with negative sales or total assets. Since computing ICCs requires analysts' earnings forecasts, the number of firms with valid information is reduced to 40,123 firm-year observations.

1.1.2 The Proxies for the Cost of Equity

We estimate the cost of equity using the CAPM, the Fama and French (1992, 1993) 3-factor model (FF3M), and the 4-factor model (FF4M, Carhart (1997)). There is no consensus about the computing procedure of the ICC in the literature. Each study makes its own specific assumptions to facilitate the computation of the ICC. We compute the ICC in three different ways for each firm, following the procedures utilized by Claus and Thomas (2001) ($ICC\text{-}CT$), Gebhardt et al. (2001) ($ICC\text{-}GLS$), and Li et al. (2013)($ICC\text{-}LNS$), respectively. We provide the detailed estimation procedures in Appendix A.

1.1.3 Return Decomposition

We first follow the methodology of Chen et al. (2013) to decompose the realized return into two components: (1) cash flow news (CFN), defined as the price change holding the discount rate constant, and (2) discount rate news (DRN), defined as the price change holding the cash flow forecasts constant. Specifically, the stock return between month t and $t+1$ can be written as follows:

$$\begin{aligned} r_{i,t} = \frac{P_{i,t+1} - P_{i,t}}{P_{i,t}} &= \frac{f\left(c_{i,t+1}, d_{i,t+1}\right) - f\left(c_{i,t}, d_{i,t}\right)}{P_{i,t}} \\ &= CFN_{i,t} - DRN_{i,t}, \end{aligned} \tag{1.1}$$

where $f(\cdot)$ is the discounted cash flow function, and $c_{i,t}$ and $d_{i,t}$ are the cash flow forecast and the discount rate of firm i at month t, respectively. The cash flow news (CFN) and discount rate news (DRN) could be expressed as:

$$CFN_{i,t} = \frac{1}{2}\left[\frac{f\left(c_{i,t+1}, d_{i,t+1}\right) - f\left(c_{i,t}, d_{i,t+1}\right)}{P_{i,t}} + \frac{f\left(c_{i,t+1}, d_{i,t}\right) - f\left(c_{i,t}, d_{i,t}\right)}{P_{i,t}}\right] \tag{1.2}$$

$$DRN_{i,t} = -\frac{1}{2}\left[\frac{f\left(c_{i,t}, d_{i,t+1}\right) - f\left(c_{i,t}, d_{i,t}\right)}{P_{i,t}} + \frac{f\left(c_{i,t+1}, d_{i,t+1}\right) - f\left(c_{i,t+1}, d_{i,t}\right)}{P_{i,t}}\right]. \tag{1.3}$$

We compound the monthly CFN and DRN to annualize over the firm's fiscal year. Since this methodology uses earnings forecasts and stock prices, it identifies forward-looking cash flow news and discount rate news by construction (Chen et al. (2013)). The ICC is also based on earnings forecasts and stock price. Therefore, to ensure that our results are not spuriously induced by common earnings forecasts, we also consider alternative methodology.

Campbell and Shiller (1988) develop an alternative methodology to decompose the stock return into CFN (related to future dividends) and DRN (related to the discount rate). The basic idea is to predict cash flows and discount rate from predictive variables, and then compute CFN and DRN as residuals. They use the vector autoregression (VAR) to generate a forecast of cash flows and discount rates. Vuolteenaho (2002) further develop this methodology to be based on the unexpected return. In particular, omitting the firm subscript i, the unexpected return can be expressed as

$$r_t - E_{t-1}(r_t) = CFN_t - DRN_t. \tag{1.4}$$

Following Vuolteenaho (2002), we estimate the components of equation (1.4) with the following VAR system of log-linear dynamic equations:

$$r_t = \alpha_1 r_{t-1} + \alpha_2 roe_{t-1} + \alpha_3 bm_{t-1} + \eta_{1t} \tag{1.5}$$

$$roe_t = \beta_1 r_{t-1} + \beta_2 roe_{t-1} + \beta_3 bm_{t-1} + \eta_{2t} \tag{1.6}$$

$$bm_t = \gamma_1 bm_{t-1} + \gamma_2 roe_{t-1} + \gamma_3 bm_{t-1} + \eta_{3t}. \tag{1.7}$$

where r is market-adjusted log stock return, roe is market-adjusted log return on equity, and bm is the market-adjusted log book-to-market ratio. This approach uses ROE as the basic cash flow fundamental to predict cash flows and discount rate.

The Campbell and Shiller (1988) approach provides a decomposition of the unexpected total equity returns, whereas the Chen et al. (2013) approach provides a decomposition of the total capital appreciation on a stock (including both expected and unexpected capital appreciation). Separating DRN and CFN from the stock return allows us to examine whether and how distinctively cost-of-equity proxies capture DRN and CFN. According to the Abel and Blanchard (1986) model, CFN is expected to have a positive effect, while DRN is expected to have a negative effect, on investment.

1.1.4 Summary Statistics

Panel A in Table 1.1 provides the summary statistics for the sample. The average (median) capital expenditure ($CAPX$) is 6.8% (4.6%) of total assets. The average net equity issuance is 11.2% of total assets and the median is mere 0.8%. Thus, firms engage in fairly active capital investment activities, while issuing equity lumpily and less frequently. The average ICC ranges from 9.8% (ICC-GLS) to 14% (ICC-LNS), while the factor model-based estimates range from 11% to 12.1%.

We report the correlation matrix for our estimates on Panel B. ICC measures and factor model-based estimates are highly correlated among themselves, respectively, but there are also significant positive correlations between factor model-based estimates and ICC measures. ICC measures have significant and positive correlations with the discount rate news but show mixed correlations with cash flow news. The CAPM estimate also shows positive correlation with the discount rate news, whereas the FFM estimates show little correlation with the discount rate news. Both the CAPM and the FFM estimates show little correlation with cash flow news.

1.2 Empirical Results

1.2.1 The Cost of Equity and Corporate Investment

In order to investigate the effect of each of the cost-of-equity proxies on corporate investment, we start with the following baseline regression model:

$$I_{i,t} = \alpha_0 + \alpha_1 R^e_{i,t-1} + \alpha_2 CF_{i,t} + \alpha_3 Q_{i,t-1} + \eta_t + \theta_i + \varepsilon_{i,t}, \tag{1.8}$$

where subscripts i and t represent firm and time, respectively. I is investment (capital expenditure scaled by beginning-of-the-year assets), R^e is the cost-of-equity proxy, CF is cash flow divided by total assets, and Q is Tobin's q. We also include firm fixed effects θ_i and year effects η_t in order to control for unobservable firm-specific characteristics and general economic trends. Detailed definitions of variables are provided in Appendix B.

Table 1.2 reports the estimation results of investment regression (1.8). The coefficient estimates on all ICC measures are significant and negative, suggesting that firms invest less when the cost of equity is higher. In contrast, the coefficient estimates on factor model-based estimates are positive and significant, suggesting that firms invest more when the cost of equity is higher. The results also show that CF and Q have significant and positive effects on investment, consistent with previous results.

In order to examine whether the ICC absorbs the explanatory power of factor model-based estimates, or vice versa, we simultaneously include both the ICC and factor model-based estimates in columns (8)-(10). The results show that the coefficient estimates change little, suggesting that both ICC and factor model-based estimates have independent and opposite effects on investment.

Our findings confirm the opposite effects of the ICC and factor model-based estimates on investment documented by Frank and Shen (2016). In the next section, we also examine their effects on equity issuance. Given that equity financing is a key channel for the effect of the cost of equity on investment (Morck et al. (1990) and Baker et al. (2003)), it is interesting to see if firms' equity issuance is also similarly affected by these alternative cost-of-equity estimates. Moreover, the literature has not yet explored this link.

1.2.2 The Cost of Equity and Net Equity Issuance

In Table 1.3, we investigate the effects of the cost-of-equity proxies on net equity issuance using the same regression model of (1.8) with the dependent variable replaced by net equity issuance. The coefficient estimates on ICC measures are all significant and negative, whereas the coefficient estimates on factor model-based estimates are positive and significant. The results also suggest that CF and q have positive effects on net equity issuance.

Our findings of the negative relations between the ICC and investment/net equity issuance suggest that firms increase their equity issuance and investment when the cost of equity is relatively low. Factor model-based estimates, however, show opposite effects. Thus, the ICC and factor model-based estimates contain information relevant not only for investment but also for equity issuance. In the next section, we try to understand the nature of information conveyed by these estimates and their opposite effects on investment and equity issuance.

1.2.3 Cash Flow News and Discount Rate News

In order to understand the contradicting effects of the ICC and factor model-based estimates, we examine their relations with the cash flow news (CFN) and discount rate news (DRN). We first examine how CFN and DRN affect investment and net equity issuance based on the following regression model:

$$Y_{i,t} = \beta_0 + \beta_1 CF_{i,t} + \beta_2 Q_{i,t-1} + \beta_3 CFN_{i,t-1} + \beta_4 DRN_{i,t-1} + \eta_t + \theta_i + \varepsilon_{i,t}. \tag{1.9}$$

where $Y_{i,t}$ is either investment or net equity issuance as used before.

Table 1.4 reports the estimation results for both investment and equity issuance. In all regressions, the coefficient estimates on CFN are positive and significant, while those on DRN are negative and significant. The results are similar whether we use the Chen et al. (2013) or Campbell and Shiller (1988) approach for the CFN-DRN decomposition. Thus, these findings confirm that CFN has positive effects, while DRN having negative effects, on investment and equity issuance decisions. These findings are consistent with Abel and Blanchard (1986) who find that the cash flow and discount rate components of q still show significant effects when added to the q-investment regression.

Given the findings of the opposite effects of CFN and DRN on investment and equity issuance, we now examine how cost-of-equity proxies are associated with CFN/DRN with the following regressions:

$$R^e_{i,t} = \alpha_0 + \alpha_1 CFN_{i,t} + \alpha_2 DRN_{i,t} + \varepsilon_{i,t}. \tag{1.10}$$

The results are reported in Table 1.5. The Chen et al. (2013) return decomposition (Panel A) and the Campbell and Shiller (1988) approach (Panel B) produce similar results. ICC measures reflect both the CFN and *DRN*. The coefficient estimates on *DRN* are positive and significant, while those on CFN are negative and significant, which suggests that the positive discount rate news and the negative cash flow news are associated with higher ICC. For the CAPM estimate, however, the coefficient estimates on both *DRN* and CFN are not significant. Moreover, for the FFM estimates, the coefficient estimates on *DRN* are negative, while those on CFN are positive.

Next, we examine if the cash flow component of factor model-based estimates indeed drive investment/financing decisions. To this end, we follow Campbell and Vuolteenaho (2004) who develop the two-beta model in which the CAPM beta is broken into two components, one reflecting news on the market's future cash flows ("bad beta") and one reflecting news on the market's discount rate ("good beta"). Following their approach, we decompose the CAPM estimate into two components in order to examine their respective effects on investment and equity issuance. We also estimate cash flow and discount rate betas for each of MKT, SMB, HML and UMD factors separately, and then use the sum of the products of cash flow (discount rate) betas and corresponding factor premiums as the cash flow (discount rate) component of the FFM expected returns.

The results in Table 1.6 show that investment and equity issuance are mainly driven by the "bad beta" reflecting news about future cash flows. Similarly, for the FFM estimates, the cash flow component is the main driver for their effects on corporate investment and financing decisions. Thus, the positive effects of the factor model-based estimates on investment and equity issuance appear to be driven by the part of the expected return associated with the market's cash flow news. These findings are consistent with previous studies showing that stock returns and betas in factor models are associated with relatively more cash flow news than discount rate news (Vuolteenaho (2002), Campbell and Vuolteenaho (2004), Campbell et al. (2010), and Chen et al. (2013)).

In sum, the findings in this section suggest that the discount rate news and cash flow news contained in the ICC and factor model-based estimates may explain their opposite effects on investment and equity issuance. We also observe that both the discount rate and cash flow news have significant but opposite effects on some of the cost-of-equity proxies. Given that the discount rate and cash flow components tend to move cyclically together (Abel and Blanchard (1986)), it is possible that the cost-of-equity proxies spuriously appear to capture both the discount rate and cash flow news when they in fact capture mainly one of them. In order to test for this suspected channel in more controlled settings, we examine their behavior around recessions and following exogenous events in the next section.

1.2.4 Behavior of the Cost-of-Equity Estimates around Recessions and Following Exogenous Events

Recessions are characterized by heightened uncertainty and risk aversion of investors (González-Hermosillo (2008), Coudert and Gex (2008), and Frank and Goyal (2009)), which increases the risk premium and thereby the discount rate. Firms may also face lower cash flows during recessions. If a cost-of-equity proxy captures the discount rate (cash flow) news, it will increase (decrease) prior to recessions. Thus, we can examine whether the cost-of-equity estimates capture the discount rate news or the cash flow news by examining their movements prior to recessions.

We first plot the time trends of the cost-of-equity proxies in Figure 1.1. IC-C measures tend to increase prior to the highlighted recession periods, while factor model-based estimates show the opposite trend. ICC measures appear to reflect the discount rate news, while factor model-based estimates appear to reflect the cash flow news stemming from the diminishing profitability during recessions.

In table 1.7, we run panel regressions with firm and year-quarter fixed effects, to test if the ICC and factor model-based estimates indeed show opposite movements prior to recessions. Our main interest is the coefficient estimate on the dummy variable for the quarter prior to recession periods. The results clearly show that the ICC increases significantly prior to recessions capturing the discount rate shocks, whereas factor model-based estimates decrease significantly prior to recessions capturing the cash flow shocks.

Taxpayer Relief Act of 1997 (TRA) and the Jobs and Growth Tax Relief Reconciliation Act of 2003 (JGTRRA) provide tax cuts in capital gains, raising the effective after-tax return for equity investors and thereby increasing the supply of equity capital. These legislations are likely to affect the cost of equity, independent of firms' decisions. Moreover, these tax cuts are not likely to have immediate impacts on firms' cash flows. Accordingly, we use these tax cuts to have a clean test whether the ICC and factor model-based estimates capture the discount rate news or not. The effects of the tax cuts on the cost of equity will depend on the elasticity of capital demand. With perfectly inelastic demand, the cost of equity will be reduced by the tax cut. With perfectly elastic demand, the cost of equity will not change. Since financially constrained firms have low demand elasticity of equity capital, they are expected to experience a larger reduction in the cost of equity following the tax cuts. Indeed, Dhaliwal et al. (2007) and Dai et al. (2013) show that these tax cuts have reduced the cost of equity particularly for financially constrained firms. Thus, we hypothesize that the cost-of-equity estimates will capture the discount rate shocks for financially constrained firms.

We test the hypothesis with the following difference-in-difference (DID) regression:

$$R^e_{i,t} = \alpha_0 + \alpha_1 Post_t + \alpha_2 HFC_i + \alpha_3 Post_t \times HFC_i + \varepsilon_{it}, \tag{1.11}$$

where $Post$ is a dummy variable that takes 1 if it is the third quarter of 1997 or 2003, and 0 if it is the first quarter of 1997 or 2003 (skipping the announcement quarter). HFC is a dummy variable which takes value of 1 if the firm is on the top 30% of financial constraint (FC) at the beginning of the year, defined as in Hadlock and Pierce (2010):[5]

$$FC_{i,t} = 0.737 \times \text{Size}_{i,t} + 0.043 \times \text{Size}^2_{i,t} - 0.04 \times \text{Firmage}_{i,t}. \tag{1.12}$$

where $Size$ is the log of total assets (replaced with log($4.5 billion) if the actual value exceeds this threshold) and $Firmage$ is the number of years since the firm's initial public offering (replaced with 37 if it exceeds 37).

Table 1.8 presents the estimation results of the DID regressions. The coefficient estimates on $Post$ are negative and significant for all three ICC measures, indicating that the cost of equity becomes lower following the discount rate shocks. The significant and negative coefficient estimates on $Post * HFC$ also

[5] We also try the KZ index as an alternative measure of financial constraint. The results are similar and not reported.

suggest that after the adoption of TRA and JGTRRA, the cost of equity decreased significantly more for financially constrained firms than for non-constrained firms. For factor model-based estimates, however, the coefficient estimates on $Post$ and $Post * HFC$ are all significant and positive, suggesting that the cost of equity is higher following the discount rate shocks and especially for financially constrained firms.

The results in Table 1.8 verify that the ICC captures the discount rate shocks, while factor model-based estimates capture the cash flow effects of the discount rate shocks. In the next section, we try to understand whether and how such information flows from the stock market to managers who make investment and financing decisions. More specifically, we want to see if the ICC contains firm-specific information on the discount rate, while factor model-based estimates contain market-wide information on cash flows from the stock market.

1.2.5 The Stock Market Information Channel

In the perfect market, q should be sufficient information for investment decision (Abel and Blanchard (1986)). In the presence of market frictions such as information asymmetry and external financing constraints, however, manager may look to additional information when making investment and financing decisions. Given that the cost of equity essentially reflects the market's assessment of the firm-specific risk contained in the stock price, a cost-of-equity proxy should inform managers about the market's assessment of their firms' risk or discount rate when making investment and financing decisions. Consequently, in this section, we seek to understand the information contained in the cost-of-equity proxies by investigating their effects on investment and equity issuance in relation to such market frictions. In particular, we investigate if the effects of alternative cost-of-equity proxies on investment and equity issuance can be explained by the information channel from the stock market to managers.

Even though the stock price-investment link has been well documented, the literature does not agree on its cause. On the one hand, Baker et al. (2003), Gilchrist et al. (2005), and Polk and Sapienza (2009) show significant effects of mis-pricing on investment. In particular, Baker et al. (2003) suggest that financially constrained or equity-dependent firms' investment is especially sensitive to mispricing in the stock market. On the other hand, Dow and Gorton (1997), Subrahmanyam and Titman (1999), and Chen et al. (2007) suggest that such effects of stock price on corporate investment reflect private information as managers are informed about their investments from the stock market. Moreover, Bakke and Whited (2010) suggest that corporate investment does not respond to stock-market mispricing nor private information but to legitimate information (q) contained in stock price movement. Nonetheless, these studies agree at least on the finding that the stock price-investment link is more pronounced for equity dependent firms and private information firms.

Since the cost of equity is a critical input from the capital market for the discount rate in the capital budgeting process, we expect that firms with more private information than those with less private information show greater sensitivity to the cost of capital for their investment and financing decisions. Similarly, equity dependent firms' investment and financing decisions are expected to show greater sensitivity to the cost of equity than non-equity dependent firms as equity dependent firms face financial constraints to fund their investment opportunities (Baker et al. (2003)). Accordingly, we examine if cost-of-equity proxies capture these patterns of the stock price-investment link as they contain information on the discount rate and cash flows from the stock market. In particular, the ICC is to capture firm-specific information on the discount rate by its design (Pastor et al. (2008) and Chen et al. (2013)). Thus, we expect that the ICC has negative effects on investment and equity issuance for firms with more private information and equity dependence. Given our findings that factor model-based estimates capture cash flow news and the previous results that they reflect market-wide information (Campbell and Vuolteenaho (2004) and Campbell et al. (2010)), we do not expect such effects for factor model-based estimates. To the extent that the stock market informs managers of the economy-wide cash flows, however, the positive effects of factor model-based estimates on investment and equity issuance may be more pronounced for non-private information and non-equity dependent firms.

Private Information

We measure the amount of private information by the price nonsynchronicity calculated as one minus R-square from the time-series regression of daily stock return on the market and 3-digit SIC industry portfolio returns over the fiscal year.[6] Chen et al. (2007) suggest that a weak correlation of a firm's stock return with the market and industry returns indicates more private information that is useful for the firm's investment decision. Based on the price nonsynchronicity measure, we define the top 30% as large private information firms and the bottom 30% as small private information firms. For the estimation of price nonsyn-

[6]This measure was first suggested by Roll (1988) and later developed by Morck et al. (2000), Durnev et al. (2003), Durnev et al. (2004), and Chen et al. (2007).

chronicity, we require that firms have at least 150 days of non-missing returns during the given year.

Table 1.9 presents the results. For investment regressions on Panels A and B, the coefficient estimates on ICC measures are all negative and significant for firms with large private information, whereas the coefficient estimates on ICC measures are all insignificant for firms with small private information. In contrast, the coefficient estimates on factor model-based estimates are all insignificant for firms with large private information, whereas they are all positive and significant for firms with small private information. For net equity issuance regressions on Panels C and D, ICC measures have significant and negative effects for large private information firms, while they have insignificant or marginal effects for small private information firms. Factor model-based estimates, in contrast, show mostly insignificant effects for large private information firms, while showing significant and positive effects for small private information firms.

The findings in this section suggest that a firm's investment and equity issuance are particularly sensitive to the ICC when there is greater amount of private information in the stock price. Thus, the ICC appears to contain information about the market's assessment of project risk beyond what is reflected in q and cash flows. However, the results for factor model-based estimates suggest that firms with less private information tend to be sensitive to the cash flow shocks in the public information set. It is also notable that the results show similar effects for equity issuance. Thus, the discount rate may inform managers of not just the timing of investment but also the timing of equity issuance.

Equity Dependence

Here, we compare the sensitivities of firms' investment and equity issuance to alternative cost-of-equity proxies between high and low equity-dependent firms. Following Baker et al. (2003) and Bakke and Whited (2010), we use the KZ index to measure equity dependence as follows:

$$KZ_{i,t} = -1.002CF_{i,t} - 39.368DIV_{it} - 1.315CASH_{i,t} + 3.139LEV_{i,t}. \tag{1.13}$$

We define firms with the top 30% KZ index as high equity-dependent and firms with the bottom 30% KZ index as low equity-dependent.

Table 1.10 presents the results. For high equity-dependent firms' investment on Panel A, we find that the coefficient estimates on ICC measures are all negative and highly significant, while those on factor model-based estimates are all insignificant. For low equity-dependent firms' investment on Panel B, the coefficient estimates on ICC measure are insignificant, while those on factor model-based estimates exhibit strong positive effects. For equity issuance on Panels C and D, the results show that ICC measures have unequivocally significant and negative effects for high equity-dependent firm, while having less significant but still negative effects for low equity-dependent firms. The negative effect of the ICC on equity issuance but insignificant effect on investment for low equity-dependent firms suggest that the low cost of equity may induce managers to issue equity that is not necessarily linked to concurrent investment. In contrast, factor model-based estimates show insignificant effects on equity issuance for high equity-dependent firms, while showing significant and positive effects for low equity-dependent firms.

The results in Table 1.10 suggest that equity-dependent firms' investment and equity issuance are particularly sensitive to the discount rate component captured by the ICC. In contrast, factor model-based estimates show significant and positive effects for non-equity-dependent firms, suggesting that financially unconstrained firms' investment and equity issuance are sensitive to the cash flow news.

Overall, firms with greater private information and equity dependence exhibit most sensitivities of their investment and equity issuance to the ICC. These findings suggest that the discount rate component contained in the ICC is important private information that affects firms' investment and equity issuance. Moreover, the significant effects of the ICC for equity dependent firms suggest that what drives the stock price-investment link is the discount rate news in the stock price. In contrast, factor model-based estimates affect investment and financing decisions for non-equity dependent and non-private information firms, which suggests that factor model-based estimates contain information on market-wide cash flows which in turn affects firms' investment and financing decisions.

1.3 Robustness Checks

1.3.1 Mergers and Acquisitions (M&A) and Research and Development (R&D)

Both theoretical and empirical studies suggest that M&As are significantly affected by stock market valuation.[7] The key component of these theoretical models is private information. Moreover, Daniel et al. (2016) argue that for non-manufacturing firms R&D is more important investment than capital expenditures, and M&As could substitute for capital expenditures and R&D. Brown et al. (2009) also show that the supply of equity has a significant effect on R&D expenditures. Consequently, we estimate our investment regressions with the dependent variable broadly defined as the sum of capital expenditure (CAPX) plus M&A and R&D scaled by beginning-of-the-year assets.

The results in Table 1.11 show that all coefficient estimates on ICC measures remain negative and highly significant, whereas those on factor model-based estimates are insignificant. To the extent that these broadly defined investments are more sensitive to the discount rate shock and private information, these findings suggest that firms' investment decisions are particularly sensitive to private information on the discount rate news captured by the ICC.

[7] Shleifer and Vishny (2003), Rhodes-Kropf and Viswanathan (2004),Rhodes-Kropf et al. (2005), and Dong, Hirshleifer, Richardson, and Teoh (2006) argue that M&As are driven by high market valuation.

1.3.2 Error-in-Variable Consistent GMM

Erickson and Whited (2000, 2002, 2012) demonstrate that a regression of investment on q is seriously misspecified because of measurement error in q. Accordingly, it is possible that our results are driven by measurement errors in q. It is also possible that the cost-of-equity proxies are subject to the errors-in-variable biases. Erickson et al. (2014) show that the high order linear cumulant estimator is asymptotically equivalent to the high order moments estimator suggested by Erickson and Whited (2000, 2002), but the former performs better in finite samples. Accordingly, we follow Erickson et al. (2014) and Erickson et al. (2015) to implement their measurement-error consistent GMM technique to correct for measurement errors in q and the cost-of-equity estimates. Specifically, we treat q and cost-of-equity proxies as misspecified variable and use fifth-order cumulants. The results (Table A.2 in the Appendix) show that our findings remain quantitatively and qualitatively the same. Thus, we rule out that the potential effects of measurement errors in q and cost-of-equity proxies drive our results.

1.3.3 Utilizing Fundamentals-based q

Cummins et al. (2006) suggest that q constructed using analysts' forecast earnings better reflects fundamentals important for investment spending. In particular, using the analysts' forecast earnings-based q rather than the stock price, they find no evidence that investment is sensitive to cash flows. Their earnings-based q is particularly interesting for our study because the ICC is also based on the same earnings forecast from analysts. If the ICC indeed captures the discount rate news embedded in the stock price beyond the information contained in q and cash flows, the effects of the ICC will remain significant. Thus, we examine if our results are altered when the earnings-based q is used.

The results (in Table A.3 in the Appendix) show that all coefficient estimates on ICC measures remain negative and highly significant, whereas those on factor model-based estimates are still positive and significant. The results are consistent with our main finding that the ICC informs managers about the discount rate, beyond q and cash flows.

1.3.4 Controlling for Other Firm Characteristics

We also investigate the effect of the cost-of-equity proxies on corporate investment while controlling for other firm characteristics, which should mitigate the concern that our cost-of-equity proxies simply capture some firm characteristics not reflected in q. For this exercise, we estimate regression (1.8) including the following additional control variables: leverage (Lev), firm size ($Size$), cash dividend (Div), fixed assets (FA), and cash holdings ($Cash$). Table 1.12 reports the results. The signs and significance of all coefficient estimates for cost-of-equity proxies remain the same as previously reported.

1.3.5 Non-Recession Periods

Given the opposite patterns of the ICC and factor-model-based estimates are particularly conspicuous around recession periods as shown in Figure 1.1 and Table 1.7, we check if the results are driven by recession periods. To this end, we run regressions after excluding the years containing the recession periods.

The results (in Table A.4 in the Appendix) based on non-recession periods show that the coefficient estimates on ICC measures are significant and negative, whereas the coefficient estimates on factor model-based estimates are positive and mostly significant. Thus, the opposite effects of the ICC and factor model-based estimates are not exclusively driven by their particular behavior around recession periods.

1.3.6 Long-term Effects

Given that some capital projects involve long-term planning and implementation, there may be a time gap between the time of estimating the cost of equity and the actual investment for a project. In order to check the potential effect of this time gap, we try longer (up to two-year) lags of the cost of equity proxies.

The estimation results with the second-year lags of the cost-of-equity proxies (in Table A.5 in the Appendix) show that the long-term effects are mostly insignificant except for the two-year lagged 4-factor model-based estimate which shows a positive and significant effect. Thus, our findings suggest that long-term effects of the cost-of-equity proxies on investment are limited.

1.4 Summary and Conclusion

When the market assesses low risk for a firm's investment opportunities, the effective cost of equity becomes lower. As a result, the firm is likely to take on more investment. One puzzling result from the empirical literature is the apparent positive relation between investment and the cost of equity, as proxied by the CAPM and the Fama-French model (FFM). Furthermore, we find that factor model-based estimates also have positive effects on equity issuance. We show that such positive effects are resulting from the fact that factor model-based estimates capture the cash flow news that has positive effects on investment and equity issuance. In contrast, the ICC, reflecting discount rate news for given forecast cash flows, show negative effects on investment and equity issuance. The ICC increases prior to recession periods capturing the discount rate news, while the factor model-based estimates decrease prior to recession periods capturing the cash flow news. Moreover, the ICC decreases following positive supply shocks in equity capital, while the factor model-based estimates show opposite effects. The ICC exhibits stronger effects for firms with more equity dependence and greater private information. In contrast, the factor model-based estimates, capturing cash flow news contained in the public information set, show positive effects on firms' investment and equity issuance.

Our findings suggest that the ICC captures the firm-specific discount rate that is contained in the stock price. It may be close to what managers come up with after considering the market conditions as it shows direct effects on investment and financing decisions. Such consideration is particularly important for more equity dependent firms that are more likely to face financial constraints and firms with greater private information that are more likely to be sensitive to the discount rate news for their investment and financing decisions. In contrast, the factor model-based estimates capture the market-wide cash flow news and positively predict corporate investment and equity issuance. The factor models seem to miss out the firm-specific discount rate news that are particularly relevant for corporate investment and financing decisions.

If we evaluate cost-of-capital proxies based on their ability to capture the discount rate that can be used for capital budgeting decisions, our results support the ICC as an alternative to the traditional factor model-based estimates. The main advantage of the ICC is that it captures the discount rate from the forward-looking perspective. Such an advantage may be particularly important in the presence of market frictions such as financing constraints and asymmetric information.

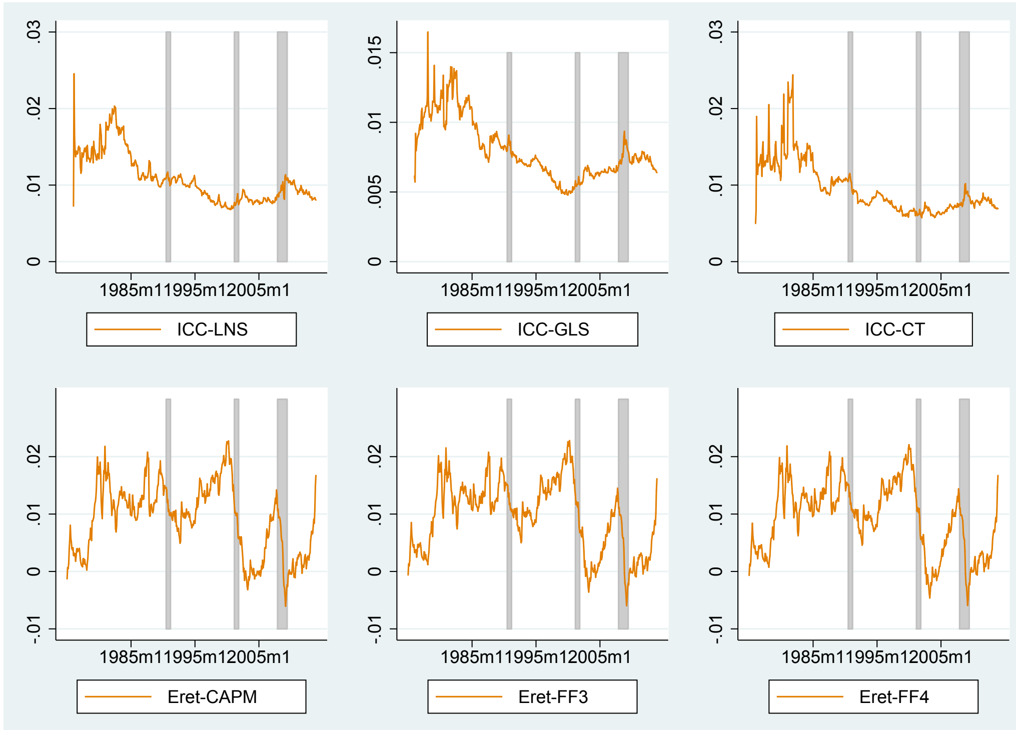


Figure 1.1: Times Series Patterns of the Cost-of-Equity Proxies

The figure shows the patterns of ICC and factor model-based expected return estimates during recession and non-recession periods. The sample consists of US firms from 1985 to 2013. ICC-LNS, ICC-GLS and ICC-CT are the implied cost of equity estimates following the methods of Li et al. (2013), Claus and Thomas (2001), and Gebhardt et al. (2001), respectively. CAPM, FF3, and FF4 are expected returns based on the CAPM, the Fama and French three-factor and four-factor models, respectively. The shaded regions are NBER recession periods.

Table 1.1: Descriptive Statistics and Variable Correlations

Panel A of the table provides the summary statistics for the variables used in the study. The sample consists of US firms from 1985 to 2013. For each variable, we report the number of observations (N), mean (Mean), standard deviation (Std), 25th percentile, median and 75th percentile. Panel B provides Pearson correlation matrix of cost-of-equity proxies and return components. ICC-LNS, ICC-GLS and ICC-CT are the implied cost of equity estimates following the methods of Li et al. (2013), Claus and Thomas (2001), and Gebhardt et al. (2001), respectively. Eret-CAPM, Eret-FF3, and Eret-FF4 are expected returns based on the CAPM, the Fama and French three-factor and four-factor models, respectively. CFN-CDZ (CFN-CS) and DRN-CDZ (DRN-CS) are cash flow news and discount rate news following the method of Chen et al. (2013) (Campbell and Shiller (1988)). Eret-Cash Flow and Eret-Discount Rate are cash-flow and discount-rate expected return components, respectively, where cash-flow beta and discount-rate beta are estimated following Campbell and Vuolteenaho (2004)'s approach. Detailed definitions of the variables are provided in Appendix B. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A. Summary Statistics

	N	Mean	S.D.	Q25	Median	Q75
CPAX	40053	0.068	0.071	0.024	0.046	0.084
CAPX+R&D	40053	0.109	0.098	0.041	0.081	0.144
Issuance	37929	0.112	0.332	-0.003	0.008	0.038
CF	40053	0.097	0.112	0.054	0.102	0.153
Q	40057	1.843	1.166	1.120	1.468	2.112
Real Q	36995	1.607	1.643	0.569	1.137	2.037
1-R^2	40123	0.753	0.209	0.634	0.812	0.919
ICC-LNS	40123	0.140	0.071	0.093	0.120	0.170
ICC-GLS	40123	0.098	0.029	0.079	0.095	0.113
ICC-CT	40123	0.110	0.063	0.078	0.097	0.123
Eret-CAPM	40123	0.110	0.094	0.028	0.112	0.170
Eret-FF3	40123	0.121	0.098	0.054	0.114	0.181
Eret-FF4	40123	0.110	0.108	0.039	0.104	0.175
CFN-CDZ	39752	0.067	0.608	-0.390	0.090	0.584
CFN-CS	37751	0.045	0.613	-0.424	0.092	0.531
DRN-CDZ	39752	-0.027	0.626	-0.566	-0.048	0.498
DRN-CS	37751	-0.004	0.534	-0.224	0.019	0.178
Eret-MKTCF	40091	0.084	0.068	0.022	0.085	0.129
Eret-MKTDR	40091	0.038	0.027	0.012	0.039	0.059
Eret-SMBCF	40091	0.045	0.044	0.018	0.041	0.064
Eret-SMBDR	40091	0.036	0.029	0.014	0.040	0.054
Eret-HMLCF	40091	0.015	0.038	-0.003	0.016	0.042
Eret-HMLDR	40091	0.032	0.023	0.010	0.034	0.049
Eret-UMDCF	40091	0.026	0.076	-0.013	0.026	0.070
Eret-UMDDR	40091	0.040	0.029	0.013	0.045	0.060

Panel B. Correlation								
	ICC-LNS	ICC-GLS	ICC-CT	Eret-CAPM	Eret-FF3	Eret-FF4	CFN-CDZ	DRN-CDZ
ICC-LNS	1.00							
ICC-GLS	0.50***	1.00						
ICC-CT	0.57***	0.58***	1.00					
Eret-CAPM	0.12***	0.09***	0.12***	1.00				
Eret-FF3	0.08***	0.06***	0.07***	0.59***	1.00			
Eret-FF4	0.03***	0.01*	0.05***	0.47***	0.85***	1.00		
CFN-CDZ	0.15***	-0.03***	0.03***	-0.00	-0.00	0.00	1.00	
DRN-CDZ	0.21***	0.06***	0.08***	0.02***	-0.00	-0.00	0.84***	1.00

Table 1.2: Estimation Results of Investment Regressions

This table provides estimation results from panel regressions. The sample consists of US firms from 1985 to 2013. The dependent variables are capital expenditures (CAPX) scaled by beginning-of-year total assets (AT). ICC-LNS, ICC-GLS and ICC-CT are the implied cost of equity estimates following the methods of Li, Ng, and Swaminathan (2013), Claus and Thomas (2001), and Gebhardt, Lee, and Swaminathan (2001), respectively. Eret-CAPM, Eret-FF3, and Eret-FF4 are expected returns based on the CAPM, the Fama and French three-factor and four-factor models, respectively. All the cost-of-equity proxies are measured at the beginning of the year. Q is Tobin's q at the beginning of the year and CF is concurrent free cash flow. All regressions include year and firm fixed effects. Detailed definitions of variables are provided in Appendix B. The robust standard errors adjusted for firm-level clustering are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Dependent Variable: CAPX										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
CF	0.102***	0.107***	0.106***	0.105***	0.105***	0.104***	0.104***	0.110***	0.109***	0.109***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Q	0.007***	0.006***	0.006***	0.007***	0.007***	0.007***	0.007***	0.006***	0.006***	0.006***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ICC-LNS		-0.036***						-0.034***	-0.034***	-0.034***
		(0.01)						(0.01)	(0.01)	(0.01)
ICC-GLS			-0.065***							
			(0.02)							
ICC-CT				-0.012*						
				(0.01)						
Eret-CAPM					0.031***			0.034***		
					(0.01)			(0.01)		
Eret-FF3						0.012**			0.016***	
						(0.00)			(0.01)	
Eret-FF4							0.014***			0.015***
							(0.00)			(0.00)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	40050	38093	38180	37503	37176	37176	37176	35420	35420	35420
Adjusted R^2	0.154	0.162	0.161	0.161	0.155	0.155	0.155	0.163	0.163	0.163

Table 1.3: Estimation Results of Net Equity Issuance Regressions

This table provides estimation results from panel regression. The sample consists of US firms from 1985 to 2013. The dependent variable is Issuance, defined as the difference of log adjusted shares outstanding between fiscal year t and $t-1$. ICC-LNS, ICC-GLS and ICC-CT are the implied cost of equity estimates following the methods of Li, Ng, and Swaminathan (2013), Claus and Thomas (2001), and Gebhardt, Lee, and Swaminathan (2001), respectively. Eret-CAPM, Eret-FF3, and Eret-FF4 are expected returns based on the CAPM, the Fama and French three-factor and four-factor models, respectively. All the cost-of-equity proxies are measured at the beginning of the year. Q is Tobin's q at the beginning of the year and CF is concurrent free cash flow. All regressions include year and firm fixed effects. Detailed definitions of variables are provided in Appendix B. The robust standard errors adjusted for firm-level clustering are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Dependent Variable: ISSUANCE									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CF	0.489***	0.480***	0.480***	0.473***	0.470***	0.470***	0.497***	0.494***	0.494***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Q	0.030***	0.031***	0.033***	0.031***	0.031***	0.031***	0.032***	0.032***	0.032***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ICC-LNS	-0.182***						-0.176***	-0.175***	-0.173***
	(0.03)						(0.03)	(0.03)	(0.03)
ICC-GLS		-0.214**							
		(0.09)							
ICC-CT			-0.046*						
			(0.03)						
Eret-CAPM				0.086*			0.100**		
				(0.04)			(0.05)		
Eret-FF3					0.093***			0.099***	
					(0.03)			(0.03)	
Eret-FF4						0.082***			0.082***
						(0.02)			(0.02)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	36103	36188	35563	35238	35238	35238	33606	33606	33606
Adjusted R^2	0.068	0.066	0.067	0.064	0.064	0.064	0.067	0.067	0.067

Table 1.4: Sensitivities of Investments and Net Equity Issuance to Cash Flow and Discount Rate News

This table provides estimation results from panel regression. The sample consists of US firms from 1985 to 2013. The dependent variables are capital expenditures (CAPX) scaled by beginning-of-year total assets (AT); and Issuance, defined as the difference of log adjusted shares outstanding between fiscal year t and $t-1$. CFN-CDZ and DRN-CDZ are cash flow news and discount rate news, respectively, according to the Chen et al. (2013)'s approach. CFN-CS and DRN-CS are cash flow news and discount rate news, respectively, according to Campbell and Shiller (1988) approach. All the cost-of-equity proxies are measured at the beginning of the year. Q is Tobin's q at the beginning of the year and CF is concurrent free cash flow. All regressions include year and firm fixed effects. Detailed definitions of variables are provided in Appendix B. The robust standard errors adjusted for firm-level clustering are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	(1) CAPX	(2) ISSUANCE	(3) CAPX	(4) ISSUANCE
CF	0.105***	0.425***	0.094***	0.382***
	(0.01)	(0.03)	(0.01)	(0.03)
Q	0.006***	0.021***	0.006***	0.021***
	(0.00)	(0.00)	(0.00)	(0.00)
CFN-CDZ	0.009***	0.145***		
	(0.00)	(0.01)		
DRN-CDZ	-0.008***	-0.143***		
	(0.00)	(0.01)		
CFN-CS			0.014***	0.132***
			(0.00)	(0.01)
DRN-CS			-0.014***	-0.118***
			(0.00)	(0.01)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	37774	35802	37698	35672
Adjusted R^2	0.164	0.084	0.160	0.076

Table 1.5: Sensitivities of Cost-of-Equity Proxies to Cash Flow News and Discount Rate News

This table provides estimation results from Fama-Macbeth regression. The sample consists of US firms from 1985 to 2013. The dependent variables include implied cost of capital measures and factor model-based proxies. ICC-LNS, ICC-GLS and ICC-CT are the implied cost of equity estimates following the methods of Li et al. (2013), Claus and Thomas (2001), and Gebhardt et al. (2001), respectively. Eret-CAPM, Eret-FF3, and Eret-FF4 are expected returns based on the CAPM, the Fama and French three-factor and four-factor models, respectively. CFN-CDZ (CFN-CS) and DRN-CDZ (DRN-CS) are cash flow news and discount rate news following the method of Chen et al. (2013) (Campbell and Shiller (1988)). Detailed variable definitions are provided in the Appendix B. The reported R^2 the the time-series average of R^2 from cross-sectional regressions. The robust standard errors adjusted for autocorrelation up to 12 years are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A. Chen et al. (2013) Return Decomposition						
	(1)	(2)	(3)	(4)	(5)	(6)
	ICC-LNS	ICC-GLS	ICC-CT	Eret-CAPM	Eret-FF3	Eret-FF4
CFN-CDZ	-0.010***	-0.012***	-0.011***	0.000	0.004**	0.008***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
DRN-CDZ	0.031***	0.012***	0.017***	-0.001	-0.005***	-0.008***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	39752	39752	39752	39752	39752	39752
R^2	0.047	0.027	0.012	0.009	0.003	0.003
Panel B. Campbell and Shiller (1988) Return Decomposition						
	(1)	(2)	(3)	(4)	(5)	(6)
	ICC-LNS	ICC-GLS	ICC-CT	Eret-CAPM	Eret-FF3	Eret-FF4
CFN-CS	-0.024***	-0.017***	-0.015***	-0.003	0.006***	0.008***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
DRN-CS	0.024***	0.017***	0.015***	0.004	-0.007*	-0.011***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	37751	37751	37751	37751	37751	37751
R^2	0.017	0.046	0.010	0.012	0.006	0.007

Table 1.6: Sensitivities of Investments and Net Equity Issuance to Cash-Flow and Discount-Rate Expected Return Components

This table provides estimation results from panel regression. The sample consists of US firms from 1985 to 2013. The dependent variables are capital expenditures (CAPX) scaled by beginning-of-year total assets (AT); and Issuance, defined as the difference of log adjusted shares outstanding between fiscal year t and $t-1$. Cash flow and discount rate component of expected returns for MKT, SMB, HML and UMD factor premium are calculated as cash-flow beta and discount-rate beta times corresponding factor premium. The cash-flow beta and discount-rate beta is estimated for MKT, SMB, HML and UMD portfolio returns following Campbell and Vuolteenaho (2004). All the cost-of-equity proxies are measured at the beginning of the year. Q is Tobin's q at the beginning of the year and CF is concurrent free cash flow. All regressions include year and firm fixed effects. Detailed definitions of variables are provided in Appendix B. The robust standard errors adjusted for firm-level clustering are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	CAPX			ISSUANCE		
	(1)	(2)	(3)	(4)	(5)	(6)
	CAPM	FF3	FF4	CAPM	FF3	FF4
CF	0.105***	0.104***	0.104***	0.473***	0.468***	0.469***
	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)	(0.03)
Q	0.007***	0.007***	0.006***	0.031***	0.031***	0.031***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Eret-Cash Flow	0.060***	0.062***	0.056***	0.180**	0.191**	0.174**
	(0.01)	(0.01)	(0.01)	(0.08)	(0.08)	(0.08)
Eret-Discount Rate	-0.036	-0.047	-0.024	-0.142	-0.185	-0.101
	(0.04)	(0.04)	(0.04)	(0.21)	(0.22)	(0.22)
Eret-SMBCF		-0.023*	-0.024*		-0.111	-0.116
		(0.01)	(0.01)		(0.08)	(0.09)
Eret-SMBDR		0.035	0.023		0.731**	0.702**
		(0.06)	(0.07)		(0.33)	(0.34)
Eret-HMLCF		0.110***	0.108***		0.986***	0.976***
		(0.02)	(0.02)		(0.14)	(0.14)
Eret-HMLDR		-0.229***	-0.237***		-1.348***	-1.374***
		(0.06)	(0.07)		(0.37)	(0.37)
Eret-UMDCF			0.014*			0.067
			(0.01)			(0.04)
Eret-UMDDR			0.032			0.045
			(0.05)			(0.28)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	37144	37144	37144	35206	35206	35206
Adjusted R^2	0.156	0.157	0.157	0.064	0.066	0.066

Table 1.7: Changes in Cost-of-Capital Estimates Prior to Recession Period

This table provides panel regression results of changes in cost-of-capital estimates on prior-to-recession dummy. The cost-of-capital estimates including implied cost of capital measure proposed by Li, Ng, and Swaminathan (2013), Claus and Thomas (2001), and Gebhardt, Lee, and Swaminathan (2001). Eret-CAPM, Eret-FF3, and Eret-FF4 are expected returns based on the CAPM, the Fama and French three-factor and four-factor models, respectively. *Prior to Recession Dummy* is an indicator which takes value of one for the one quarter before NBER recession periods, and zero otherwise. The sample is at firm-quarter level. The robust standard errors adjusted for firm clustering are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	ICC-LNS	ICC-GLS	ICC-CT	Eret-CAPM	Eret-FF3	Eret-FF4
Prior to Recession Dummy	0.002***	0.001***	0.002***	-0.011***	-0.011***	-0.003***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Firm FE	Y	Y	Y	Y	Y	Y
Year-Quater FE	Y	Y	Y	Y	Y	Y
Observations	78100	78100	78100	78100	78100	78100
Adjusted R^2	0.008	0.035	0.019	0.542	0.402	0.383

Table 1.8: Difference-in-Difference Estimation for Cost-of-Equity Proxies

This table provides estimation results of the difference-in-difference (DID) regression. The sample consists of US firms in 1997 and 2003. The dependent variables are six cost-of-equity measures. ICC-LNS, ICC-GLS and ICC-CT are the implied cost of equity estimates following the methods of Li, Ng, and Swaminathan (2013), Claus and Thomas (2001), and Gebhardt et al. (2001), respectively. Eret-CAPM, Eret-FF3, and Eret-FF4 are expected returns based on the CAPM, the Fama and French three-factor and four-factor models, respectively. We estimate the following DID regression:

$$R^e_{i,t} = \alpha_0 + \alpha_1 Post_t + \alpha_2 HFC_i + \alpha_3 Post_t \times HFC_i + \varepsilon_{it},$$

where Post is a dummy variable that takes 1 if it is the third quarter of 1997 or 2003, and 0 if it is the first quarter of 1997 or 2003. HFC is a dummy variable which takes value of 1 if the firm is on the top 30% of financial constraint in the last year. The measure of financial constraint is defined as

$$FC_{i,t} = \Pr\left(\text{Financial Constraint}\right) = 1 - \frac{1}{1 + \exp\left(\beta' X_{i,t} - 0.454\right)}$$

and

$$\beta' X_{i,t} = 0.737 \times \text{Size}_{i,t} + 0.043 \times \text{Size}^2_{i,t} - 0.04 \times \text{Firmage}_{i,t}$$

Detailed variables definitions are provided in the Appendix B. The robust standard errors adjusted for firm-level clustering are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	(1) ICC-LNS	(2) ICC-GLS	(3) ICC-CT	(4) Eret-CAPM	(5) Eret-FF3	(6) Eret-FF4
Post	-0.004*	-0.007***	-0.009***	0.021***	0.026***	0.034***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
HFC	0.028***	0.014***	0.014***	-0.026***	-0.027***	-0.037***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
Post*HFC	-0.008**	-0.005***	-0.007**	0.010***	0.031***	0.035***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	2638	2638	2638	2638	2638	2638
Adjusted R^2	0.032	0.082	0.018	0.022	0.044	0.046

Table 1.9: Price Informativeness and Investment/Financing Sensitivity

This table provides estimation results from panel regressions. The sample consists of US firms from 1985 to 2013. The dependent variable is capital expenditures (CAPX) scaled by beginning-of-year total assets (AT) and equity issuance, defined as the difference of log adjusted shares outstanding between fiscal year t and $t-1$. Panel A and C include firms with price nonsynchronicity measure in the top 30%, and Panel B and D include firms with price non-synchronicity measure in the bottom 30%. The price nonsynchronicity is calculated as 1-R^2, where R^2 is the R-square of time-series regression of daily stock returns on market and 3-digit SIC industry returns at year t. ICC-LNS, ICC-GLS and ICC-CT are the implied cost of equity estimates following the methods of Li et al. (2013), Claus and Thomas (2001), and Gebhardt et al. (2001), respectively. Eret-CAPM, Eret-FF3, and Eret-FF4 are expected returns based on the CAPM, the Fama and French three-factor and four-factor models, respectively. All the cost-of-equity proxies are measured at the beginning of the year. Q is Tobin's q at the beginning of the year, and CF is concurrent free cash flow. All regressions include year and firm fixed effects. Detailed definitions of variables are provided in Appendix B. The robust standard errors adjusted for firm-level clustering are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Investment for Large Private Information Firms						
	(1)	(2)	(3)	(4)	(5)	(6)
CF	0.110***	0.109***	0.105***	0.102***	0.102***	0.102***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Q	0.005***	0.005***	0.006***	0.005***	0.005***	0.005***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ICC-LNS	-0.039***					
	(0.01)					
ICC-GLS		-0.065**				
		(0.03)				
ICC-CT			-0.017*			
			(0.01)			
Eret-CAPM				0.020		
				(0.02)		
Eret-FF3					0.008	
					(0.01)	
Eret-FF4						0.013
						(0.01)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	8471	8482	8263	8448	8448	8448
Adjusted R^2	0.096	0.096	0.094	0.091	0.090	0.091

Panel B: Investment for Small Private Information Firms						
	(1)	(2)	(3)	(4)	(5)	(6)
CF	0.160***	0.158***	0.157***	0.166***	0.161***	0.161***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Q	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ICC-LNS	-0.023					
	(0.01)					
ICC-GLS		0.023				
		(0.04)				
ICC-CT			0.006			
			(0.02)			
Eret-CAPM				0.096***		
				(0.02)		
Eret-FF3					0.039***	
					(0.01)	
Eret-FF4						0.032***
						(0.01)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	8954	8991	8882	8514	8514	8514
Adjusted R^2	0.209	0.207	0.207	0.208	0.204	0.204

Panel C: Financing for Large Private Information Firms						
	(1)	(2)	(3)	(4)	(5)	(6)
CF	0.362***	0.360***	0.337***	0.339***	0.342***	0.342***
	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
Q	0.017***	0.018***	0.023***	0.017***	0.017***	0.017***
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
ICC-LNS	-0.151***					
	(0.04)					
ICC-GLS		-0.192**				
		(0.08)				
ICC-CT			-0.056*			
			(0.03)			
Eret-CAPM				-0.150**		
				(0.07)		
Eret-FF3					-0.046	
					(0.04)	
Eret-FF4						-0.026
						(0.04)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	7789	7802	7601	7775	7775	7775
Adjusted R^2	0.038	0.037	0.036	0.034	0.034	0.034

Panel D: Financing for Small Private Information Firms						
	(1)	(2)	(3)	(4)	(5)	(6)
CF	0.586***	0.579***	0.589***	0.591***	0.562***	0.560***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.06)	(0.07)
Q	0.043***	0.046***	0.044***	0.045***	0.047***	0.047***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ICC-LNS	-0.098					
	(0.07)					
ICC-GLS		0.401*				
		(0.24)				
ICC-CT			0.019			
			(0.07)			
Eret-CAPM				0.540***		
				(0.10)		
Eret-FF3					0.277***	
					(0.07)	
Eret-FF4						0.164***
						(0.06)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	8723	8756	8651	8293	8293	8293
Adjusted R^2	0.103	0.103	0.103	0.103	0.102	0.101

Table 1.10: Equity Dependence and Investment/Financing Sensitivity to COE Proxies

This table provides estimation results from panel regression. The sample consists of US firms from 1985 to 2013. The dependent variable is capital expenditures (CAPX) scaled by beginning-of-year total assets (AT) and equity issuance, defined as the difference of log adjusted shares outstanding between fiscal year t and $t-1$. Panel A and C include firms with the top 30% of equity dependence, and Panel B and D include firms with the bottom 30% of equity dependence. The equity dependence is measured by KZ index, defined as

$$KZ_{i,t} = -1.002CF_{i,t} - 39.368DIV_{it} - 1.315CASH_{i,t} + 3.139LEV_{i,t}.$$

ICC-LNS, ICC-GLS and ICC-CT are the implied cost of equity estimates following the methods of Li et al. (2013), Claus and Thomas (2001), and Gebhardt et al. (2001), respectively. Eret-CAPM, Eret-FF3, and Eret-FF4 are expected returns based on the CAPM, the Fama and French three-factor and four-factor models, respectively. CFN-Chen (CFN-CS) and DRN-Chen (DRN-CS) are cash flow news and discount rate news following the method of Chen et al. (2013) (Campbell and Shiller (1988)). All the cost-of-equity proxies are measured at the beginning of the year. Q is Tobin's q at the beginning of the year and CF is concurrent free cash flow. All regressions include year and firm fixed effects. Detailed definitions of variables are provided in Appendix B. The robust standard errors adjusted for firm-level clustering are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Investment for High Equity-dependent Firms						
	(1)	(2)	(3)	(4)	(5)	(6)
CF	0.121***	0.122***	0.124***	0.133***	0.132***	0.132***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Q	0.022***	0.020***	0.021***	0.020***	0.021***	0.021***
	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
ICC-LNS	-0.040***					
	(0.01)					
ICC-GLS		-0.121***				
		(0.04)				
ICC-CT			-0.023**			
			(0.01)			
Eret-CAPM				0.025		
				(0.02)		
Eret-FF3					-0.003	
					(0.01)	
Eret-FF4						-0.002
						(0.01)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	10247	10234	10045	9850	9850	9850
Adjusted R^2	0.157	0.155	0.154	0.152	0.151	0.151
Panel B: Investment for Low Equity-dependent Firms						
	(1)	(2)	(3)	(4)	(5)	(6)
CF	0.080***	0.079***	0.071***	0.069***	0.068***	0.068***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Q	0.004***	0.004***	0.005***	0.004***	0.004***	0.004***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ICC-LNS	-0.009					
	(0.01)					
ICC-GLS		0.025				
		(0.03)				
ICC-CT			0.012			
			(0.01)			
Eret-CAPM				0.047***		
				(0.01)		
Eret-FF3					0.025***	
					(0.01)	
Eret-FF4						0.026***
						(0.01)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	9916	9954	9792	9725	9725	9725
Adjusted R^2	0.171	0.171	0.171	0.165	0.164	0.165

Panel C: Financing for High Equity-dependent Firms						
	(1)	(2)	(3)	(4)	(5)	(6)
CF	0.374***	0.372***	0.391***	0.397***	0.395***	0.396***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Q	0.056***	0.056***	0.056***	0.056***	0.056***	0.056***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
ICC-LNS	-0.193***					
	(0.04)					
ICC-GLS		-0.357***				
		(0.13)				
ICC-CT			-0.067*			
			(0.04)			
Eret-CAPM				0.034		
				(0.09)		
Eret-FF3					-0.007	
					(0.05)	
Eret-FF4						0.007
						(0.04)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	9435	9425	9261	9074	9074	9074
Adjusted R^2	0.050	0.048	0.048	0.048	0.048	0.048

Panel D: Financing for Low Equity-dependent Firms						
	(1)	(2)	(3)	(4)	(5)	(6)
CF	0.507***	0.497***	0.493***	0.481***	0.478***	0.478***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Q	0.029***	0.029***	0.031***	0.029***	0.029***	0.029***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ICC-LNS	-0.171***					
	(0.04)					
ICC-GLS		-0.174				
		(0.11)				
ICC-CT			-0.056*			
			(0.03)			
Eret-CAPM				0.097*		
				(0.05)		
Eret-FF3					0.113***	
					(0.03)	
Eret-FF4						0.101***
						(0.03)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	26618	26713	26251	26094	26094	26094
Adjusted R^2	0.075	0.074	0.075	0.070	0.071	0.071

Table 1.11: Estimation Results of Investment Regressions Including R&D and M&A Expenses

This table provides estimation results from panel regressions. The sample consists of US firms from 1985 to 2013. The dependent variable in Panel A is capital expenditures (CAPX) plus M&A expenses (AQC) scaled by beginning-of-year total assets (AT). The dependent variable in Panel B is R&D expenses (XRD) and M&A expenses (AQC) scaled by beginning-of-year total assets (AT). ICC-LNS, ICC-GLS and ICC-CT are the implied cost of equity estimates following the methods of Li et al. (2013), Claus and Thomas (2001), and Gebhardt et al. (2001), respectively. Eret-CAPM, Eret-FF3, and Eret-FF4 are expected returns based on the CAPM, the FF3M, and the FF4M. All the cost-of-equity proxies are measured at the beginning of the year. Q is Tobin's q at the beginning of the year, and CF is concurrent free cash flow. All regressions include year and firm fixed effects. Detailed definitions of variables are provided in Appendix B. The robust standard errors adjusted for firm-level clustering are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Dependent Variable: CAPX+M&A						
	(1)	(2)	(3)	(4)	(5)	(6)
CF	0.191***	0.187***	0.188***	0.189***	0.189***	0.189***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Q	0.008***	0.008***	0.009***	0.009***	0.009***	0.009***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ICC-LNS	-0.105***					
	(0.01)					
ICC-GLS		-0.191***				
		(0.03)				
ICC-CT			-0.060***			
			(0.01)			
Eret-CAPM				-0.002		
				(0.02)		
Eret-FF3					-0.005	
					(0.01)	
Eret-FF4						0.005
						(0.01)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	38093	38180	37503	37176	37176	37176
Adjusted R^2	0.071	0.069	0.068	0.066	0.066	0.066
Panel B: Dependent Variable: CAPX+R&D+M&A						
	(1)	(2)	(3)	(4)	(5)	(6)
CF	0.189***	0.182***	0.180***	0.182***	0.182***	0.182***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Q	0.014***	0.014***	0.015***	0.016***	0.016***	0.016***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ICC-LNS	-0.093***					
	(0.01)					
ICC-GLS		-0.156***				
		(0.03)				
ICC-CT			-0.046***			
			(0.01)			
Eret-CAPM				-0.005		
				(0.02)		
Eret-FF3					-0.005	
					(0.01)	
Eret-FF4						0.002
						(0.01)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	38093	38180	37503	37176	37176	37176
Adjusted R^2	0.084	0.082	0.081	0.080	0.080	0.080

Table 1.12: Estimation Results of Investment/Financing Regressions with Additional Controls

This table provides estimation results from panel regressions. The sample consists of US firmss from 1985 to 2013. The dependent variable is capital expenditures (CAPX) scaled by beginning-of-year total assets (AT) and equity issuance, defined as the difference of log adjusted shares outstanding between fiscal year t and $t-1$. ICC-LNS, ICC-GLS and ICC-CT are the implied cost of equity estimates following the methods of Li, Ng, and Swaminathan (2013), Claus and Thomas (2001), and Gebhardt, Lee, and Swaminathan (2001), respectively. Eret-CAPM, Eret-FF3, and Eret-FF4 are expected returns based on the CAPM, the Fama and French three-factor and four-factor models, respectively. All the cost-of-equity proxies are measured at the beginning of the year. Q is Tobin's q at the beginning of the year, CF is concurrent free cash flow. Additional control variables include: Lev = Book value of debt/ market value of asset, where the book value of debt equals long-term debt (DLTT) plus debt in current liabilities(DLC) and the market value of asset (MVA) equals total asset (AT) plus closing stock price (PRCC) times common shares outstanding(CSHO) minus common equity(CEQ) minus deferred taxes(TXDB); $Size$ =Natural log of total assets, where total assets is inflated to 1996 dollars using the GDP deflator; Div = Cash dividend divided by total assets; FA = Net plant, property, and equipment scaled by total assets; and $Cash$ = Cash and short-term investments over total assets. Detailed definitions of variables are provided in Appendix B. The robust standard errors adjusted for firm-level clustering are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Investment						
	(1)	(2)	(3)	(4)	(5)	(6)
CF	0.096***	0.095***	0.094***	0.095***	0.093***	0.094***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Q	0.006***	0.006***	0.006***	0.006***	0.006***	0.006***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Lev	-0.005	-0.005	-0.005	-0.005	-0.005	-0.005
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Size	-0.011***	-0.011***	-0.011***	-0.010***	-0.010***	-0.010***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Div	-0.029***	-0.032***	-0.032***	-0.023*	-0.023*	-0.023*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
FA	0.033***	0.033***	0.032***	0.020**	0.020**	0.020**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Cash	0.001	0.002	0.002	0.001	0.001	0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ICC-LNS	-0.040***					
	(0.01)					
ICC-GLS		-0.072***				
		(0.02)				
ICC-CT			-0.019***			
			(0.01)			
Eret-CAPM				0.033***		
				(0.01)		
Eret-FF3					0.012**	
					(0.00)	
Eret-FF4						0.014***
						(0.00)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	No	No
Observations	37956	38042	37368	37012	37012	37012
Adjusted R^2	0.183	0.181	0.181	0.171	0.170	0.171

Panel B: Financing						
	(1)	(2)	(3)	(4)	(5)	(6)
CF	0.456***	0.449***	0.451***	0.436***	0.434***	0.434***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Q	0.028***	0.028***	0.030***	0.029***	0.029***	0.029***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Lev	0.008**	0.007**	0.008**	0.006*	0.006*	0.006*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Size	-0.040***	-0.040***	-0.040***	-0.044***	-0.043***	-0.043***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
Div	-0.293***	-0.287***	-0.288***	-0.241***	-0.242***	-0.241***
	(0.09)	(0.09)	(0.09)	(0.08)	(0.08)	(0.08)
FA	0.059***	0.058***	0.060***	0.033*	0.033*	0.033*
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Cash	0.023*	0.028**	0.028**	0.028**	0.028**	0.028**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
ICC-LNS	-0.203***					
	(0.03)					
ICC-GLS		-0.246***				
		(0.09)				
ICC-CT			-0.078***			
			(0.03)			
Eret-CAPM				0.092**		
				(0.04)		
Eret-FF3					0.088***	
					(0.03)	
Eret-FF4						0.078***
						(0.02)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	No	No
Observations	35976	36062	35439	35088	35088	35088
Adjusted R^2	0.071	0.070	0.071	0.068	0.068	0.068

CHAPTER 2

THE ECONOMIC CONSEQUENCES OF MUTUAL FUND ADVISORY MISCONDUCT

2.1 Introduction

The impact of misconduct in the mutual fund industry has received wide attention over the past decade. The number of misconduct cases peaked around 2003-2005, when a group of mutual fund advisors were alleged for late trading that breached fiduciary duties and violated securities laws. The late trading scandals caused significant economic damage to investors, with average annualized losses up to $400 million between 1998 and 2003 Zitzewitz (2006). The academic literature on mutual funds shows that misconduct has significant negative effect on future fund flows Houge and Wellman (2005); Choi and Kahan (2007); Potter and Schwarz (2012); Qian and Tanyeri (2017), and fund returns McCabe (2009); Chapman-Davies et al. (2015). Given the large economic consequences of misconduct for mutual funds, the SEC places great emphasis on combating against misconduct of investment advisors. Therefore, understanding the role of misconduct in mutual fund industry provides important policy implications for financial regulation.

My paper is the first to conduct a comprehensive study on the impact of all mutual fund misconduct events on fund flows. Prior academic literature mainly focuses on late trading scandals around 2003-2005 with data from news media, such as Wall Street Journal Choi and Kahan (2007); McCabe (2009); Qian and Tanyeri (2017), so they miss a lot of other misconduct events. My paper covers a broad set of mutual fund advisory misconduct cases collected from Form ADV, a novel database which has not been widely used in the mutual fund literature. The Form ADV contains rich information of fund advisors in the United States, including their historical misconduct record. To be clear, my paper includes all types of mutual fund advisory misconduct, not limited to late trading scandals. In addition to investigating fund investors' response to misconduct, I also examine post-misconduct changes in advisory contracting. The reactions from mutual fund companies provide valuable insights for addressing agency issues in mutual fund industry.

To do empirical analysis, I construct a monthly panel dataset containing fund flows, misconduct indicator and several advisor characteristics. Form ADV has been used in prior studies to identify malfeasant hedge funds Brown et al. (2008), to estimate the operational risk of hedge funds Brown et al. (2012), and to predict fraud of investment managers Dimmock and Gerken (2012). My paper is the first to look into each misconduct case with more detailed information from the Regulatory Disclosure Reporting Page of Form ADV.[1] The forms of mutual fund advisory misconduct include, but are not limited to, undisclosed compensation schemes from mutual fund companies, unlicensed employees or branches, unsuitable investment advice and unauthorized trades. Among them, the most prevalent form is market timing and late (after-hour) trading. To get accurate fund flow data I merge Form ADV with N-SAR filings using a unique advisor identifer. N-SAR filings are semi-annual reports for investment companies. The unique strength of this filing is that it includes monthly gross mutual fund flow, which is a direct measure of dollar value of inflows and outflows for each fund. Examining the effect of advisory misconduct on inflows and out-

[1]Although advisors may engage in misconduct associated with different products (equity, insurance, options, etc), I focus exclusively on the mutual fund advisory misconduct, since we have relatively rich information for the mutual funds industry.

flows separately tells us how existing mutual fund shareholders and outside investors respond to the misconduct.

My analysis begins with evaluating the impact of advisory misconduct on advisors' fund flows. I run panel regression using the full sample of mutual fund advisory misconduct events from 2000-2013. Specifically, the dependent variable, advisors' cumulative netflows up to 24 months following misconduct, is regressed on a misconduct indicator, along with other advisor characteristics. The misconduct indicator equals one if an advisor commits at least one mutual fund advisory misconduct in month t, and zero otherwise. The result shows that misconduct is associated with a 5% abnormal reduction in flows per annum, or about 40 million U.S. dollars for a median advisor. Moreover, I find that the negative effect of misconduct is mainly driven by increased outflows rather than reduced inflows. This implies that existing fund investors in general are "news watchers" and respond to the innovation in misconduct information.

Although the baseline result estimates an average effect of advisory misconduct on fund flows, it suffers from potential endogeneity problem, due to endogenous nature of misconduct timing, as well as heterogeneity among advisors with and without misconduct. To address these concerns, I corroborate the baseline result with evidence concerning the causal effect of advisory misconduct on fund flows. A mandate introduced by the SEC provides a quasi-natural experiment that I use for this purpose.

On September 12, 2000, the SEC proposed an electronic filing mandate effective in January 2001, requiring investment advisors to file the Form ADV electronically to the Investment Adviser Registration Depository (IARD).[2] The

[2]The website address is https://www.adviserinfo.sec.gov/IAPD/default.aspx.

SEC mandate aims to eliminate many costs advisers incur in filing their Form ADV, improving disclosure procedure and facilitating information flows.[3] As a consequence, investors have much easier access to the information of advisors, including historical misconduct in the past ten years. In comparison, before the mandate people have to contact advisors or regulatory agencies to obtain paper copies of disclosure documents to know advisors' historical misconduct information, and that is time-consuming and costly. This policy change offers a quasi-natural experiment to examine the disclosure effect of advisory misconduct in the mutual fund industry.

In the event study, I estimate the cumulative treatment effect around this mandate with 12 months of pre- and post-event periods. The treatment group is defined as advisors with at least one mutual fund advisory misconduct case reported in Form ADV as of January 2001, while the control group includes advisors without any mutual fund advisory misconduct case as of the same point in time.[4] I further match the two groups of advisors based on assets under management. The purpose of matching is to reduce the observable heterogeneity among these two groups of advisors, since the exogenous shock from the mandate only tackles exclusion restriction issues. My underlying assumption is that if investors care about misconduct, then treated advisors will experience greater outflows following the revelation of their historical misconduct cases. The result corroborates the initial finding with much larger economic magnitude. The regression based on the matched sample estimates a treatment effect of 18% in one year following the mandate, suggesting a strong detrimental effect of advisory misconduct on advisors' aggregate flows. The result also lends strong support

[3]Detailed discussion on the cost-benefit analysis of the SEC electronic filing mandate can be found at https://www.sec.gov/rules/final/ia-1897.htm.

[4]Note that Form ADV contains historical misconduct information in the past ten years, so treatment advisors may have misconduct cases back to 1990s.

for the importance of information transparency in fighting against misconduct.

In addition to investigating fund investors' response to misconduct, I also examine how mutual fund companies react to mitigate the adverse effect of misconduct on flows. Kuhnen (2005) and Warner and Wu (2005) show that mutual fund companies revise advisory contract terms based on past performance and other non-performance characteristics. Therefore, I investigate whether mutual fund companies change fees, incentives and investment policies to protect themselves from misconduct. I find that following misconduct, mutual fund companies raise marketing expenditures through increased 12b-1 fees, especially for payment to underwriters. This suggests an increase in marketing efforts to alleviate damages to the firms' image resulting from advisory misconduct. I also find that there is a reduction in contractual incentives, measured by Cole's Incentive Rate and two other incentive variables, for funds managed by malfeasant advisors. This reaction discourages advisors from taking excessive risk. Finally, based on the investment policy in the N-SAR filings, I show that investment restrictions on options, futures and foreign equities are more likely to be lifted following misconduct.

The response of mutual fund companies to alleviate the negative impact of advisory misconduct go beyond revising specific contract terms. It is a natural extension to examine how advisory misconduct affects advising relationships and advisor survival. This is because mutual fund companies may deem it necessary to replace current malfeasant advisors with new ones, when the costs of associating with malfeasant advisors outweigh the benefits. Therefore, I investigate whether malfeasant advisors face more uncertainty in maintaining advising relationship with mutual fund companies, and as a consequence, are more likely to be driven out of business in the end. Overall, I document an increased likelihood of advisor replacement in the year subsequent to misconduct.[5] It demonstrates that by replacing malfeasant advisors, mutual fund companies are able to shield themselves from on-going damage to funds flows. In the similar vein, I find a significantly higher probability of business failure for malfeasant advisors through takeovers, in forms of either M&A or succession. The mutual fund investors suffer economically with 7% return under-performance over the next two years following advisory misconduct, especially during market upturns. This suggests that the purpose of relaxing investment restrictions is more likely to enable portfolio hedging activities, rather than levering up for higher future returns.

My paper contributes to three strands of literature. First, it is closely related to studies concerning misconduct in the mutual fund industry. For example, prior literature focuses on 2003-2005 mutual fund trading scandals and documents the negative impact on flows Houge and Wellman (2005); Zitzewitz (2006); Choi and Kahan (2007); Qian and Tanyeri (2017). My paper extends existing research with a broad sample of misconduct cases, and highlights information transparency as disciplinary forces against misconduct. My findings are generally supportive of advisory oversight given widespread malfeasance in asset management industry Kwan et al. (2016); Egan et al. (2016). Second, it is also related to studies on mutual fund advisory contracting. The tendency to reduce contractual incentives for advisors following misconduct is in line with Massa and Patgiri (2009) which relates high-incentive contracts to more risk-taking investments, and Warner and Wu (2011) which finds reduced compensation rate

[5]One such example is that Deutsche Investment Management Americas (the advisor) was replaced by the Korea Fund, Inc. (the mutual fund company) in 2007 after being alleged for failure to disclose potential conflict of interest to the fund board and investors. The fund company hired RCM Capital Management as its new advisor.

for funds involved in market-timing scandals in 2004. My evidence of advisor replacement is also consistent with Jenkinson et al. (2016) which highlights the importance of soft factors in fund manager selection. Finally, my paper is complement to several recent studies on how compromised trust affects asset flows Gurun et al. (2017); Kostovetsky (2016). For instance, Gurun et al. (2017) exploits a negative shock in trust among residents living in communities subject to Madoff Ponzi scheme, while Kostovetsky (2016) argues that ownership changes of mutual fund companies lead to loss of clients' trust and increased outflows. The mutual fund advisory misconduct cases vary in the extent of severity, some of which are not necessarily associated with trust busting.[6] My paper contributes to this strand of literature by showing how mutual fund companies respond to mitigate the negative effects of misconduct.

2.2 Data and Summary Statistics

2.2.1 Data Sources

The data used in this paper come from two major sources: N-SAR filings and Form ADV. I include all mutual funds covered in N-SAR filings from 2000-2013. N-SAR filings are semi-annual reports for investment companies, which contain fund and advisor identifications, monthly gross inflows and outflows, advisory contract terms, fees, investment objectives, and financial statement items such as income and expenses. The unique advantage of the N-SAR filing is that it has monthly gross fund flow, which is a direct measure of dollar value of inflows

[6]For instance, minor violation in disclosure procedure can be treated as unprofessional or incompetence.

and outflows for each fund. I download N-SAR filings from EDGAR and use natural language processing technique to extract all the data from original filings.[7] Form N-SAR/A covers the first six months of fiscal year, while N-SAR/B covers the full fiscal year. Therefore, I use data in N-SAR/B for mutual fund characteristics, and both N-SAR/A and N-SAR/B for monthly flows.

Form ADV is Uniform Application for Investment Advisor Registration. All investment advisors in the United States regulated by the Investment Advisor Act of 1940 must file this form if one of the following conditions is satisfied: (a)upon initial registration; (b)at the end of fiscal year; (c)whenever there is a material change to business. It contains information for investment advisors on several dimensions, including identification, business description, assets under management, clientele, employees, ownership structure, and disciplinary actions in the past ten years. In order to examine the impact of misconduct on fund flows, I extend the methodology of Debaere and Evans (2015) and use a two-step approach to merge Form ADV with N-SAR filings to get accurate fund flow data. Specifically, in the first step I use advisor's SEC number to unambiguously match the two datasets. The unique advisor identifier in both sources facilitates the matching process. In the second step I match the remaining advisors by their legal company names. The two-step matching process leaves with about 83% (192,003 out of 229,288) of fund-year observations in N-SAR sample. This mutual fund sample covers nearly 90% of aggregate mutual fund net assets as of 2013.[8]

Figure 2.1 shows a typical organization structure of mutual fund advisory

[7] The original Python code was developed by Robert Parham. I revised his code to expand variable coverage. My updated version is available at http://www.kaiwufinance.com/datacode.html.

[8] The aggregate net assets of investment companies are obtained from Investment Company Fact Book at http://www.icifactbook.org/ch1/17_fb_ch1#investment.

business. A mutual fund family usually consists of several mutual fund companies (trusts), each of which has numerous mutual funds. Mutual fund companies file Form N-SAR to disclose information for each individual fund. They delegate portfolio management to investment advisors and pay advisory fees. Advisors have discretion to manage portfolios for single or multiple mutual fund companies, and they file Form ADV to the SEC.[9]

2.2.2 Sample Construction

To investigate the effect of advisory misconduct on fund flows, I construct a monthly panel dataset containing fund flows, misconduct indicator and other control variables at the advisor level. Advisors' monthly fund inflows, outflows and netflows are constructed using N-SAR Item 28 and 75. N-SAR filings identify the total dollar amount of shares sold and redeemed in each month for individual mutual fund. Following the methodology of Edelen (1999) and Frazzini and Lamont (2008), I define advisor's aggregate netflows as difference between gross NAV of shares sold (*Inflow*) less gross NAV of shares redeemed (*Outflow*) for all funds under management, scaled by gross fund TNA in month t:[10]

$$Netflow_{i,t} = \frac{Inflow_{i,t} - Outflow_{i,t}}{TNA_{i,t}} \tag{2.1}$$

The reason of aggregating fund flows at advisor level is that mutual fund advisors care about aggregate revenue from total assets under management, since the reallocation of flows among funds under management has minor effect on

[9]For illustrative purpose, Figure A.1 presents examples of two advisors who manage mutual funds belonging to the Vanguard family: Wellington Management Company and Mellon Capital Management. It suggests that a fund family may employ multiple advisors in charge of portfolio management service.

[10]N-SAR Item 75 reports the average fund TNA over the reporting period. I use this item as the fund TNA for each month during the period.

the total revenue. However, for robustness checks I also conduct analysis at fund level, and the results remain quantitatively similar.[11]

Instead of obtaining fund returns from CRSP Mutual Fund Database, I calculate fund returns from N-SAR directly to avoid loss of observations in the matching process. Edelen et al. (2008) argues that prior studies are able to match only 40-50% of fund-month observations.[12] Therefore, all the fund-related variables are obtained directly from N-SAR filings. In particular, I follow the definition in Edelen et al. (2008) to calculate annual mutual fund returns using net asset values (N-SAR Item 74-V1) and fund distributions (N-SAR Items 73-A1,73-B, 73-C):

$$Return_{i,t} = \frac{NAV_{i,t} + Payout_{i,t} - NAV_{i,t-1}}{NAV_{i,t-1}} \tag{2.2}$$

Similarly, advisors' returns are calculated as TNA-weighted average returns of all funds under management.

The regulatory disclosure contains detailed history of disciplinary actions for advisors and their affiliates, including case initiator, principal sanction, principal product, and resolutions.[13] I define mutual fund advisory misconduct as malfeasant behaviors on mutual funds that leads to disciplinary actions from regulatory agencies. The main explanatory variable Mutual Fund Misconduct Dummy equals one if an advisor commits at least one mutual fund advisory misconduct.

I also add several advisor characteristics that are prominent in driving flows.

[11]The regression result at fund level is available upon request.

[12]Although using improved matching algorithm Chernenko and Sunderam (2016) reports a 70% matching rate in terms of fund-month observations and 80% in dollar terms, their methodology is not available to the public.

[13]Table A.7 provides some cases of mutual fund advisory misconduct during the sample period.

Larger funds are expected to attract more fund inflows Chevalier and Ellison (1997); Sirri and Tufano (1998); Barber et al. (2005); Bhojraj et al. (2012), hence advisor AUM is included as a control variable. I also control for firm age, which has been taken into consideration in most of the mutual fund studies. I further introduce three fee rates variables to capture the impact of cost on fund flows, including expenses ratio, front-end load and redemption fees. Finally, to account for heterogeneity in fund investment styles, I calculate average flow to fund styles as in Huang et al. (2007), where styles are categorized into domestic equity (capital appreciation, growth and income, total return), domestic bond, foreign equity, foreign bond, balanced, equity index, bond index and others based on N-SAR investment style classification.

2.2.3 Summary Statistics

Figure 2.2 presents time-series frequency of mutual fund advisory misconduct by case initiation date. There is a sharp increase in number of misconduct cases from 2003-2005 with annual average over 150. This coincides with an episode well known for prevalent mutual fund market timing and late trading scandals. After that, the number gradually declines over time to around 20 cases in recent years. It seems that mutual fund advisory misconduct doesn't exhibit strong intensity during 2008-2009 financial crisis. This may imply that poor market performance is not the only trigger for advisors' malfeasance. Nevertheless, the declining trend of misconduct does not necessarily implies that the financial regulation is no longer important. Combating against fraud and misconduct in asset management industry is still among the top priorities of the SEC.[14]

[14]The financial deregulation following Dodd-Frank Act delegated oversight responsibility for mid-size investment advisors ($25M-$100M in AUM) from the SEC to state-securities regulators.

The breakdown of advisory misconduct is shown in Table A.6. Panel A reports the percentage of misconduct cases by product types. There are altogether 18,276 advisory misconduct cases, of which 1,033 (6%) are associated with mutual funds. The low percentage is consistent with the fact that mutual fund advisors only account for 10% of all investment advisors.[15] Panel B shows that among all 1,033 mutual fund advisory misconduct cases, 39% are investigated by state regulation authorities, 26% by the SEC and 23% by the Self-Regulatory Organizations (SRO). In terms of sanction, Panel C reports that 47% of the mutual fund advisory misconduct cases end up in civil/administrative penalties, followed by 16% in cease and desist and 12% in censure. Panel D demonstrates the percentage of cases by resolution. 24% of the cases are resolved by settlement, followed by consent (21%) and acceptance, waiver & consent (19%). Panel E shows that most of the cases are filed against firms as legal entities (46%) or affiliates (46%). Finally, Panel F reports the percentage of misconduct events by content of allegation. Since there is no explicit classification of misconduct by allegation in the Form ADV, I manually review the allegation of each case and categorize them into three broad types related to transaction, disclosure and compliance. In particular, transaction-related misconduct refers to market timing/late trading scandals, or unauthorized trades; disclosure-related misconduct is related to undisclosed material information; compliance-related misconduct stands for violating relevant compliance requirement such as registration. The result shows that about 70% of the misconduct is related to compliance, followed by transaction (18%) and disclosure (13%).

Summary statistics of main variables are presented in Table 2.1. Panel A

Kwan, Charoenwong, and Umar (2016) shows that following Dodd-Frank Act, state regulators are less able to detect misconduct than the SEC.

[15] However, they employ a large proportion of finance professionals and manage over 50% of AUM in asset management industry.

reports summary statistics at the fund level. The average monthly netflows is 0.79%, with inflows (outflows) of 6.55% (5.89%). The mean of annual fund return is 2.74%, with large standard deviation of 24.49%. Average fund total net assets is 1.28 billion dollars, and average fund age is 5.2 years. Similarly, Panel B reports summary statistics at the advisor level. The mean aggregate netflows and returns are almost identical to those at fund level. On average, advisors have 20.33 billion dollars of assets under management, 220 employees, 3,180 clients, 19,780 accounts, and 2.62 firm branches.[16] The investment style variables in Panel B are percentage of net assets belonging to particular investment style in aggregate net assets managed by an advisor. It shows that nearly 50% of the assets belong to equity funds, followed by bonds funds (22%).

2.3 Empirical Results

2.3.1 Predicting Mutual Fund Advisory Misconduct

Before examining the economic consequences of advisory misconduct, I begin by exploring the determinants of advisory misconduct with a predictive model. While Dimmock and Gerken (2012) examines predictability for all types of advisory misconduct, I focus exclusively on predicting mutual fund advisory misconduct. However, their methodology serves as reasonable benchmark for my study. Therefore, I extend their model by accounting for another important factor: the regional fraud culture. Specifically, following Shumway (2001) and Rahaman (2014), I run following Logit regression with advisor-year observa-

[16]The large standard deviation of clients and accounts indicates that some mutual fund advisors also provide advisory service for a large number of individual clients.

tions from 2000-2013:[17]

$$
\begin{aligned}
Pr\{Misconduct_{i,t+1}\} = \alpha &+ \beta_1 PastMisconduct_{i,t} + \beta_2 PastRegulatory_{i,t} \\
&+ \beta_3 RegionalMisconductIntensity_{j,t} + \gamma X_{i,t} + \theta_t + \epsilon_{i,t}
\end{aligned}
\tag{2.3}
$$

In addition, to facilitate coefficient interpretation I also estimate a linear probability model.

The main explanatory variables are divided into two categories. First, I consider historical advisory misconduct, including past mutual fund advisory misconduct (*Past Mutual Fund Misconduct*) and past misconduct of all products (*Past Regulatory*). These measures capture the advisors' tendency to commit similar misconduct in the future given their historical behaviors. Another explanatory variable that is absent in Dimmock and Gerken (2012) is Regional Misconduct Intensity, defined as total number of historical mutual fund advisory misconduct cases scaled by the population in a Zipcode region. It stems from the idea that fraud culture has been recognized as one of the most important driving forces for corporate misconduct Liu (2016). Parsons et al. (2016) finds that misconduct rates of neighboring firms increase a firm's likelihood of committing financial misconduct. I also include year fixed effects to account for general business cycles during the sample period.

Table 2.2 provides result of linear probability and Logit model for predicting mutual fund advisory misconduct. Consistent with Dimmock and Gerken (2012), past regulatory action and civil/criminal penalties are strong predictors for mutual fund advisory misconduct. The coefficient of *Past Regulatory* is 0.0338, with t-statistics over 4 in Column (1). It suggests that mutual fund advisors with misconduct records are associated with 3.4% higher probabili-

[17] Shumway (2001) proves that under certain regularity conditions, a multi-period Logit model is equivalent to the discrete-time hazard model, when log of firm age is added along with other covariates.

ty to commit mutual fund advisory misconduct in the next year. The effect of civil/criminal penalties is also large and significant. One possible explanation is that malfeasant advisors are more willing to employ investment representatives with misconduct background Egan et al. (2016). I add a measure of regional fraud culture in Column (2) and (4), which is regional misconduct intensity, and find that it is positive and highly significant. The coefficient of *Regional Misconduct Intensity* in Column (2) is 0.0148 (t-statistics=2.27), suggesting that other things equal, one additional historical mutual fund advisory misconduct case per 1,000 people in the Zipcode region as of year t is associated with 1.4% higher probability of misconduct for the advisor in the following year.

In terms of control variables, past flows are insignificant at any conventional level, although the sign of coefficient is consistent with expectation that higher netflows would alleviate the propensity to engage in misconduct. Additionally, probability of misconduct increases in firm size and decreases in average account size, indicating that misconduct activities are concentrated in large advisory firms with small account size.

2.3.2 Panel Regression

I conduct the analysis for the effect of misconduct on fund flows using a broad set of mutual fund advisory misconduct cases. The sample consists of advisor-month observations from 2000-2013. The baseline panel regression framework is formulated as follows:

$$Flows_{i,t+n} = \alpha + \beta Mutual\ Fund\ Misconduct\ Dummy_{i,t} + \gamma X_{i,t} + \eta_t + \epsilon_{i,t} \quad (2.4)$$

where the dependent variable $Flows_{i,t+n}$ denotes cumulative aggregate netflows of advisor i from month t up to month $t+n$, n=1, 2, 3, 6, 12, 18 and 24 months. The primary explanatory variable Mutual Fund Misconduct Dummy equals one if an advisor commits at least one mutual fund advisory misconduct in month t, and zero otherwise. The control variables include past flows, returns, fee rates, AUM, and firm age. I also include average flow to fund styles to account for heterogeneity in advisors' exposure to different investment styles.[18] The regression also includes month fixed effects and the robust t-statistics are clustered by advisor and month. In line with the hypothesis, if mutual fund advisory misconduct adversely affects advisors' aggregate flows, I would expect to find a significant and negative coefficient β. Similary, to examine differential effect of misconduct on flows, I also run separate regressions for inflows and outflows.

The result of panel regressions are presented in Table 2.3. Panel A shows that mutual fund advisory misconduct is associated with a significant reduction in netflows over the subsequent periods. To be specific, the coefficient of *Mutual Fund Misconduct Dummy* is -0.0482 for the cumulative aggregate netflows up to month $t + 12$, suggesting that an advisor who commits mutual fund advisory misconduct in month t is going to have 5% lower cumulative netflows over the next year. Since the median gross TNA is 830 million, this translates to about 40 million dollars for a median advisor. By decomposing netflows into inflows and outflows, Panel B and Panel C demonstrates that the reduced netflows are primarily driven by increased outflows rather than reduced inflows, as the coefficient of *Mutual Fund Misconduct Dummy* in Panel C is positive and highly significant at 5% level. It indicates that existing fund investors pay attention to the innovation in misconduct information and withdraw assets out of funds managed by malfeasant advisors. Similarly, Figure 2.3 plots the aver-

[18]Specifically, it is calculated as weighted average of flows to fund style for an advisor, where the flow to fund style is average netflow of funds with the same investment style, and the weight is proportion of TNA with a particular style in total TNA managed by an advisor.

age netflows and the 95% confidence interval over the subsequent 24 months. The figures clearly show that the impact of misconduct on advisors' aggregate cumulative netflows is large and persistent, with deteriorating cumulative netflows over time. Furthermore, I find that the negative impact mainly comes from outflows following misconduct, while there are almost no changes in inflows. My findings are consistent with Chapman-Davies et al. (2015) and Qian and Tanyeri (2017) which document similar reductions in fund flows following advisory misconduct. In sum, I find strong evidence in support of the negative effect of mutual fund advisory misconduct on fund flows. The effect is statistically significant and economically sizable, mainly driven by increased outflows.

2.3.3 Event Study

Although the baseline result shows the negative effect of advisory misconduct on fund flows, it is subject to potential endogeneity problem. There are two major sources of confoundedness. First, the timing of misconduct is under discretion of fund advisors, as we expect that they are more likely to be engaged in malfeasant behaviors when past performance is low, or fund is experiencing outflows. Second, there is heterogeneity between advisors with and without misconduct. The systematic difference in size, age, and clientele all possibly drive the result in the baseline regression.

To address these concerns, I conduct a quasi-natural experiment using the SEC electronic filing mandate effective in January 2001. The mandate requires the SEC-registered investment advisors to file Form ADV electronically on the Investment Adviser Registration Depository (IARD). It generates an exogenous shock to the misconduct disclosure requirement, leading to increase in information transparency in the asset management industry. Along with reduced barrier to information transmission, fund investors have much easier access to the advisors' historical misconduct records. Therefore, I hypothesize that when past misconduct is suddenly revealed to the public following the SEC mandate, there will be a reduction in fund flows to malfeasant advisors.

I define January 2001 as the event date with 12 months of pre- and post-event periods. The treatment group is defined as advisors who have at least one mutual fund advisory misconduct case reported in the Form ADV as of January 2001, while control group includes advisors without any mutual fund advisory misconduct case as of the same point in time.[19] The regression framework is formulated as follows:

$$Flows_{i,t} = \alpha + \delta Treatment_{i,t} + \sum_{t=-4}^{4}\{\beta_t Qtr_t \times Treatment_{i,t} + \gamma_t Qtr_t\} + X_{i,t} + \epsilon_{i,t} \tag{2.5}$$

where $Flows_{i,t}$ is cumulative aggregate netflows of advisor i from quarter t=-4 up to quarter t, and Qtr_t is dummy variable for quarter t. The event month is set to be the base period and thus is omitted. Vector X includes a series of advisor characteristics, such as log of advisor's total AUM, log of firm age, log of past monetary fine, average fund returns and average flows to fund style. The standard errors are clustered by advisor and month. The coefficients β_t estimate the cumulative treatment effect over time.

Although the policy shock from the SEC mandate is considered exogenous, the treatment and control advisors are not randomly selected. The difference in characteristics between treatment and control advisors makes regression result vulnerable to omitted variable bias, as the treatment effect may be driven

[19] The emphasis here is that the misconduct events can take place before 2001. What we care about is the existence of historical misconduct cases reported on the Form ADV as of January 2001 when the electronic filling mandate became effective.

by heterogeneity in advisors' observable or unobservable attributes. To address this concern, I employ one-to-five nearest neighbourhood matching based on advisors' AUM in 2000. Altogether there are 19 treatment and 79 control advisors.[20]

Figure 2.4 reports advisors' cumulative aggregate netflows for treatment and control advisors around the SEC electronic filing mandate. Panel A shows result for the unmatched sample. Although cumulative flows grow steadily, the parallel trend assumption is not strictly satisfied prior to the event. The result for the matched sample is shown in Panel B. It demonstrates a parallel trend for the flows of two groups of advisors prior to 2001. In particular, I find a large treatment effect of the SEC mandate, as the cumulative netflows to the treated advisors are much lower than control advisors, whose flows continue to grow after the mandate became effective. Panel C reports the cumulative treatment effect and the 95% confidence interval over the 12-month window. I find that the cumulative treatment effect is not statistically different from zero before the mandate. However, it quickly drops below zero following the mandate, and is highly significant at 5% level during most of the post-event period. The cumulative treatment effect amounts to 18% in one year after the mandate.

Table 2.4 provides result of cumulative treatment effect around the SEC electronic filing mandate. Panel A reports the result for the unmatched sample. It shows that the cumulative treatment effect is significantly positive prior to the event after controlling for advisor characteristics, and it turns to be significantly negative following event date. Although the result indicates a significant treatment effect of the mandate, the significant treatment effect in the pre-treatment

[20] I choose a caliper of 0.3 in propensity score matching. The reason to apply multiple neighbourhood matching is due to the small sample of treatment advisors. I also use one-to-three matching and the result is qualitatively similar.

period indicates possible bias due to firm heterogeneity. I repeat the analysis based on the matched sample and the result is shown in Panel B. I find that the cumulative treatment effect for the matched sample is insignificant in the pre-treatment period, and becomes significantly negative following the mandate, with coefficient of *Post*Qtr(+3,+4)* in Column (1)-(2) ranging from -0.126 to -0.176, both of which are significant at 1% level. The economic magnitude of the treatment effect is sizable as well, suggesting 13%-18% reduction in cumulative aggregate netflows in the fourth quarter following the mandate. This is more than twice the magnitude in Kostovetsky (2016), which finds around 7% decline of fund flows within one year following ownership changes of mutual fund companies. In addition, by decomposing netflows into inflows and outflows, I examine the effect of misconduct for each component in Column (3)-(6). I find significant treatment effect for inflows and outflows separately, and there is larger magnitude of increase in outflows. The result also suggests that increase in information transparency could serve as disciplinary forces against malfeasant advisors in the mutual fund industry.

To check whether the treatment and control advisors are similar in observable attributes after matching process, Panel C reports result for testing covariates balance. It shows that all the selected major observable attributes are not statistically different from each other after matching. Finally, as a falsification test, Panel D reports result of a placebo test which arbitrarily sets January 1998 as event date. This placebo test aims to ensure that the observed change is mostly due to the SEC mandate, as opposed to some alternative shocks. I find that the cumulative treatment effect in the placebo test is not significant around the artificial event date, indicating that the treatment effect is unlikely to be driven by other events other than the SEC mandate effective in early 2001.

2.3.4 Robustness Checks

Excluding 2003-2005 Market Timing/Late Trading Scandals

As is shown in Figure 2.2, mutual fund advisory misconduct cases were clustered around 2003-2005, during which time mutual fund market timing and late trading scandals were prevalent Chapman-Davies et al. (2015); Qian and Tanyeri (2017). Therefore, the primary result may be driven by the misconduct during this period. To rule out this possibility, it is critical to check whether the main findings remain intact when partial sample is excluded from the analysis. As a result, I replicate the regressions in Table 2.3 by excluding observations from 2003-2005.

Table 2.5 presents the regression results. Overall, I find that the negative effect of advisory misconduct on advisors' aggregate cumulative netflows remains qualitatively similar without 2003-2005 episode of market timing and late trading scandals. Specifically, the variable of interest *Mutual Fund Misconduct Dummy* is still negative and highly significant at the 5% level in most of the specifications over the next 24 months. It suggests that the main findings are not likely to be driven by a subset of misconduct events occurred within a certain short period of time.

Quarterly Flows

In the panel regression I use the exact month of ADV filing date to construct mutual fund misconduct indicator. However, there might be time lags in information disclosure and transmission, creating uncertainty for the timing of misconduct. To address this concern, I evaluate the effect of mutual fund advisory misconduct on advisors' aggregate netflows at quarterly frequency. To be specific, I estimate similar panel regression as Equation 2.4, where the dependent variable is advisors' cumulative aggregate netflows for the next eight quarters. Correspondingly, the main explanatory variable *Mutual Fund Misconduct Dummy* is an indicator equals one if at least one mutual fund advisory misconduct case occurs in quarter t.

Table 2.6 presents the result of panel regressions at quarterly frequency. Consistent with previous findings with advisor-month observations, I find that *Mutual Fund Misconduct Dummy* is negative and highly significant in most of the specifications. In particular, advisors who commits mutual fund advisory misconduct in the current quarter t experience 2% (3%) reduction in cumulative aggregate netflows up to next 4(8) quarters. Although statistically significant, the economic magnitude is smaller than those in monthly regression. This is due to the conservative nature of the estimate provided by the quarterly regression, because we would miss the first two months of flows if the misconduct event occurs at the beginning of the quarter.

Omitted Variable Bias

So far my examinations address endogeneity issue in the baseline result. However, my finding may still suffer from unobservable firm characteristics that is omitted in the panel regressions. To address the potential omitted variable bias, I further include advisor fixed effects in the panel regression to account for time-invariant unobservable firm characteristics that affect fund flows.

Table 2.7 reports the result of panel regressions with advisor fixed effects. I find that introducing advisor fixed effects reduces both statistical significance and economic magnitude of the main explanatory variable *Mutual Fund Misconduct Dummy*. The result shows a reduction of 1.4% in aggregate flows over the next 6 months following misconduct. It indicates that under rather strict conditions, the negative effect of misconduct on flows is still statistically significant over a short-term period.

In sum, the result of robustness checks confirms the finding that mutual fund advisory misconduct plays a significant part in affecting fund flows, and the relationship holds even after excluding 2003-2005 market timing/late trading scandals. The negative impact remains qualitatively similar when the analysis is conducted at quarterly frequency, and when omitted variable bias is partially addressed with advisor fixed effects.

2.4 Further Discussions

2.4.1 Fees and Contractual Incentives

The economic consequences of mutual fund advisory misconduct are not limited to fund flows. Additional analysis on the changes in advisory contracting is of paramount interest as well. As a usual business practice, mutual fund companies negotiate with advisors on specific contract terms for fees and incentives, which in turn has profound implications for advisors' investment decisions. The bargaining process between the two parties gives rise to several testable hypothesis. First, as a counteracting measure to reduce outflows, we expect to find increased marketing expenditures. In other words, mutual fund companies are going to allocate more resources to marketing activities, leading to increased 12b-1 fees. Second, contractual incentives are expected to decrease after advisory misconduct in order to discourage advisors from inflating portfolio returns through misconduct, such as inappropriate investments with excessive risk. Chevalier and Ellison (1997) and Massa and Patgiri (2009) find that funds with high-incentive contracts deliver persistently higher risk-adjusted returns, and high-incentive contracts induce advisors to take excessive risk and put funds' survival in peril. Warner and Wu (2011) also documents compensation reductions by fund families involved in 2003-2005 market timing scandals.

To measure contractual incentives, I follow the definition in Massa and Patgiri (2009) for Cole's Incentive Rate (Cole's IR), Weighted Incentive Rate (Weighed IR) and Dollar Incentive Rate (Dollar IR). These incentive measures capture the shape, in particular, the concavity of the compensation contract. First, Cole's IR is calculated as difference between the last and first fee rates (N-SAR Item 48) over the effective fee rate.[21] It equals zero for funds with linear compensation rates and is negative for funds with concave inventive contracts. Second, Weighted IR is calculated as asset-weighted average of the fee rate divided by the first applicable fee rate. It equals one for a linearly compensated contract and less than one for a concave incentive contract. Finally, Dollar IR is calculated as difference between the last and the first fee rate multiplied by total net assets of the fund times the flow-performance sensitivity of mutual funds belonging to the same investment style in a given year. It measure the absolute dollar value advisors receive from fund flows resulting from a 1% increase in

[21]The first and last fee rates stand for the fee rate for the first and last asset bracket in the Item 48. Effective fee rate is effective marginal compensation rate based on current net assets of the fund, calculated as actual gross advisory fee advisor receives scaled by total net assets.

portfolio returns. All three contractual incentive variables increase along with incentive schemes.[22]

Table 2.8 provides regression result of changes in fees and contractual incentives following mutual fund advisory misconduct. The analysis is done at fund-year level, because the decision to revise the contract terms are made by the mutual fund companies for each fund, thus aggregating these outcome measures at advisor level would reduce a lot of variations. I add fund and year fixed effects to account for time-invariant firm characteristics and general pattern of business cycles.

Column (1)-(3) of Table 2.8 report the effect of mutual fund advisory misconduct on fees, in particular, the marketing expenditures. The result shows that mutual fund companies tend to raise marketing expenditures for funds managed by malfeasant advisors, through increased 12b-1 fees. Specifically, funds managed by malfeasant advisors have a 0.3 percentage point increase in 12b-1 fee. This may be a reaction aimed to neutralize reputation damage to the mutual fund companies. Further decomposition of 12b-1 fee in Column (2)-(3) shows that the increase in marketing effort is attributed to higher payment to underwriters. The proportion of 12b-1 fee paid to underwriters increases by 0.7 percentage point, with t-statistics of 4, while proportion paid to broker/dealer declines by 0.2 percentage point.[23] The result from changes in fees demonstrates the capabilities of marketing efforts in mitigating adverse impact of advisory misconduct.

[22]The mean of Cole's IR, Weighted IR, and Dollar IR is -0.08, 0.96 and -5.75 respectively, quantitatively similar to Massa and Patgiri (2009).

[23]Underwriters act as representatives between mutual funds and third parties selling funds. Apart from payments to underwriters and brokers/dealers, I find no significant changes in other parts of 12b-1 fees, including fees paid for advertising, sales personnel and others.

In Column (4)-(6), for all three incentive ratios, I find a significant reduction in contractual incentives following advisory misconduct. For instance, advisors committing advisory misconduct in year t experience nearly 6% reduction in Cole's IR for funds under management in the subsequent year, indicating a large effect of misconduct on incentive schemes. In similar vein, result in Column (5)-(6) shows that there is a 0.18% (15%) reduction in Weighted (Dollar) Incentive Rate in the year following misconduct. The result of changes in contractual incentives lends support to the significant and sizable effect of mutual fund advisory misconduct on funds' incentive schemes.

2.4.2 Investment Restrictions

Next, I examine how investment restrictions change and how various investment vehicles are actually used following advisory misconduct. Primarily there are two competing hypotheses concerning investment restrictions. On one hand, the disciplinary hypothesis postulates that mutual fund companies generally impose stricter investment restrictions to restrain portfolio managers from excessive speculation following misconduct. In this case, there is higher likelihood of explicit restrictions on derivative products in their investment policies. On the other hand, the hedging hypothesis proposes that mutual fund companies would allow for more freedom on the use of complex vehicles following misconduct, because derivatives help hedge against unfavorable price impact due to potential asset fire sales. Under hedging hypothesis, mutual fund companies tend to relax investment restrictions to allow for trading derivative products.

To test these two competing hypotheses, I estimate the following linear probability model with fund-year observations from 2000-2013:[24]

$$\begin{aligned} Restriction_{i,j,t+1} &= \alpha + \beta Mutual\ Fund\ Misconduct\ Dummy_{i,t} + \gamma X_{i,t} + \delta_s + \theta_t + \epsilon_{i,t} \\ Usage_{i,j,t+1} &= \alpha + \beta Mutual\ Fund\ Misconduct\ Dummy_{i,t} + \gamma X_{i,t} + \delta_s + \theta_t + \epsilon_{i,t} \end{aligned} \tag{2.6}$$

where the dependent variable $Restriction_{i,j,t+1}$ and $Usage_{i,j,t+1}$ denotes prohibition and actual usage of investment vehicle j for fund i in year $t+1$, respectively. The investment vehicles include options, futures, and foreign equities. I obtain the information of investment restrictions and actual usage from N-SAR Item 70. Both models include fund style and year fixed effects. If mutual fund advisory misconduct leads to prohibiting investment restrictions and actual investment in vehicle j, we expect to find a positive and significant β.

Table 2.9 provides result of linear probability model of investment restrictions and actual usage of investment vehicles on mutual fund advisory misconduct. From Column (1)-(3), I find that following advisory misconduct there is a reduction in probability of investment restrictions on option, futures and foreign equities. It suggests that mutual fund companies tend to relax investment restrictions on some investment vehicles to enable hedging activities. This is in line with the findings of Natter et al. (2016) and Evans, Ferreira, and Porras Prado (2017a), which contend that less restrictive investment policies help reduce portfolio risk and expand feasible investment space for fund managers. Similarly, Column (4)-(6) shows that there is higher likelihood of actual investment in options and foreign equities following misconduct. It suggests that these vehicles are more likely to be used to realize the hedging purpose.[25]

[24] The result of Logit model is quantitatively similar and is available upon request.

[25] There are several prior studies concerning the effect of derivative usage on mutual fund performance. Although Clifford et al. (2014) finds that using complex investment vehicles does not necessarily lead to higher mutual fund performance, Natter et al. (2016) demonstrates that bond funds using options have higher risk-adjusted returns, mainly due to superior investment capabilities. Besides, Almazan et al. (2004) argues that investment restrictions are more prevalent when it is difficult or less economically feasible to monitor managerial behaviors directly.

2.4.3 Advising Relationships

The responses of mutual fund companies to alleviate the negative impact of advisory misconduct are not limited to revising specific contract terms. It has been shown that the advisory misconduct imposes a significant negative impact on fund flows, resulting in pressure on the revenues of mutual fund companies as it reduces fund's total net assets. Therefore, it is a natural extension to examine how misconduct affects advising relationships between advisors and mutual fund companies. More specifically, when the costs of associating with malfeasant advisors outweigh the benefits, mutual fund companies will go beyond changing contract terms. Instead, they would replace the current advisors with new ones in order to restore profitability. To test this hypothesis, I estimate the following linear probability/Logit model with fund-year observations from 2000-2013:

$$Replacement_{i,t+1} = \alpha + \beta Mutual\ Fund\ Misconduct\ Dummy_{i,t} + \gamma X_{i,t} + \delta_s + \theta_t + \epsilon_{i,t} \tag{2.7}$$

where the dependent variable $Replacement_{i,t+1}$ is an indicator equal to one if the current fund advisor for fund i is replaced by a new advisor in year $t+1$. The model includes fund style and year fixed effects. If mutual fund advisory misconduct is associated with higher likelihood of advisor replacement, we would expect to find a positive and significant coefficient β.

Table 2.10 provides the result of linear probability and Lgoit model of advisor replacement on mutual fund advisory misconduct. The coefficient of the main explanatory variable *Mutual Fund Misconduct Dummy* in Column (1)-(2) is about 0.013, with t-statistics over 3. It suggests that advisors who commits mutual fund advisory misconduct in year t are associated with 1.3% higher probability of being replaced in year $t+1$. Therefore, the result is supportive of the hypothesis that mutual fund companies protect themselves by disassociating with malfeasant advisors.

2.4.4 Advisor Survival

Since mutual fund companies tend to replace malfeasant advisors following misconduct, advisors thus face greater uncertainty in maintaining current advising relationships, making it more difficult to provide investment advisory services and sustain profitability in the future. Therefore, I hypothesize that advisors with recent advisory misconduct are more likely to go out of business. To test this hypothesis, I estimate the following linear probability/Logit model with advisor-year observations from 2000-2013:

$$Exit_{i,t+1} = \alpha + \beta Mutual\ Fund\ Misconduct\ Dummy_{i,t} + \gamma X_{i,t} + \theta_t + \epsilon_{i,t} \tag{2.8}$$

where the dependent variable $Exit_{i,t+1}$ takes two forms: business closure and takeover. Form ADV-W contains detailed de-registration information for investment advisors, including the reason for withdrawal from SEC registration. I define *Closure* as an indicator equals one if the withdrawal reason is "firm no longer in business or closing business", and zero otherwise; and *Takeover* as an indicator equals one if the reason for de-registration is "firm sold, acquired, or merged with another investment adviser firm" or "withdrawing due to a succession", and zero otherwise.[26] The model includes year fixed effects.

Table 2.11 reports result of linear probability and Logit model of advisors' business failure on mutual fund advisory misconduct. I find significantly higher probability of business failure for malfeasant advisors, through either M&A or succession, with coefficient of 0.0302 in Column (2), which is statistically significant at 10% level. Similar finding can be found in Column (4), in which the coefficient is highly significant at 1% level. In terms of economic magnitude, it indicates that mutual fund advisory misconduct in year t leads to 3% increase

[26]After October 2009, Form ADV-W adopts a new form version which classifies the reason for withdrawn in 14 categories. However, prior to October 2009 Form ADV doesn't have check boxes for withdrawn reason. Thus I use textual analysis to classify the open-ended responses into the same 14 categories to keep consistent over time.

in probability of acquisition (succession) in year $t+1$. The economic magnitude demonstrates a large negative effect of advisory misconduct on advisors' firm survival. Interestingly, I find no significant effect of misconduct on the probability of business closure, literally the physical shutdown of the firm. It suggests that absorbing malfeasant advisors with fading brand names becomes popular in the mutual fund industry. A possible explanation is that the malfeasant advisors are potential targets of M&A/succession, as their client networks and other facilities are still valuable to other competitors.

2.4.5 Advisor Performance

The previous section has shown that advisory misconduct is followed by significant reduction in fund netflows. In this section I examine whether advisory misconduct adversely affect advisors' performance. The effect of advisory misconduct on portfolio performance is partially due to asset fire sales, liquidating securities on short notice at unfavorable prices. The significant outflows following misconduct create greater redemption pressure, forcing portfolio managers to sell a portion of assets beyond the cash reserve to meet liquidity needs, resulting in higher transaction cost and lower portfolio returns. It is also due to loss of talented fund managers, as those involved in the misconduct will be fired quickly Egan et al. (2016).

Table 2.12 reports regression result of advisors' future aggregate returns on mutual fund advisory misconduct. I find that mutual fund advisory misconduct is associated with 3.8% lower advisors' returns in the next year, which is significant at 10% level. The effect grows even larger with 8.3% reduction in cumulative returns in the next two years following misconduct. It indicates that advisory misconduct not only damages advisors' revenue by reducing the size of assets under management, but also causes economic losses for fund investors through lower fund returns.[27] Moreover, I split the sample into market upturns and downturns, where the market upturn is defined as period from 2003-2006 and 2009-2013, while the market downturn is defined as period from 2000-2002 and 2007-2008. I find that the return underperformance of malfeasant advisors mostly occurs during market upturn, which is consistent with the previous finding that mutual fund companies tend to relax investment restrictions to enable portfolio hedging activities, thus imposing limit on the upside potential for portfolio returns in a up-trending market.

Overall, I find that to mitigate the negative effect of mutual fund advisory misconduct on fund flows, mutual fund companies tend to raise marketing expenditures, reduce contractual incentives and relax investment restrictions in the subsequent years. Advisory misconduct also adversely affects advising relationships and advisor survival. Fund investors suffer economically from lower fund returns following misconduct.

2.5 Conclusion

Financial misconduct has been widely recognized as one of the important issues in the asset management industry. I comprehensively evaluates the economic consequences of advisory misconduct by estimating the effect of publicly dis-

[27] I do not use TNA-weighted average of fund alpha because it involves rolling estimation using monthly fund returns from CRSP Mutual Fund Database. To address this concern, I also test the hypothesis using fund-year observations with fund style-year fixed effects, and the result is quantitative similar.

closed regulatory actions of mutual fund advisors on fund flows. A novel Form ADV database is used to collect a broad set of mutual fund advisory misconduct cases, which includes other types of misconduct not covered by the previous literature. In addition to investigating investors' response to misconduct, I also examine how mutual fund companies react to mitigate the adverse effect of misconduct on flows. To address the potential endogeneity of misconduct, I conduct an event study around the SEC electronic filing mandate that significantly increased the transparency of advisory misconduct.

I find a significant negative effect of mutual fund advisory misconduct on fund flows. The full-sample panel regression shows a 5% reduction in fund flows to malfeasant advisors in one year following the misconduct. The effect is economically sizeable and statistically significant, and is also persistent over the subsequent 24 months, mainly through increased outflows. In addition, event study using the SEC electronic filing mandate offers new evidence on the causal effect of advisory misconduct on fund flows. The SEC mandate effective in January 2001 creates a positive shock to the information transparency for registered investment advisors. Based on a matched sample, I find that advisors with historical misconduct records witness an 18% reduction in flows in one year following the mandate. This is the first paper that uses such a policy shock in the quasi-natural experiment setting. It also demonstrates the significance of information disclosure in fighting against misconduct.

Apart from investors' response to mutual fund advisory misconduct, I also examine how mutual fund companies react to mitigate the adverse effect of misconduct on flows. In particular, I find that following misconduct, mutual fund companies tend to raise marketing expenditures, reduce contractual incentives and relax investment restrictions for investment vehicles such as options, futures and foreign equities. The malfeasant advisors face more vulnerable advising relationships and higher likelihood of business failure. Investors also suffer economically from lower portfolio returns as a result of misconduct. Overall, my paper highlights the significant impact of misconduct on fund flows and advisory contracting in the mutual fund industry.

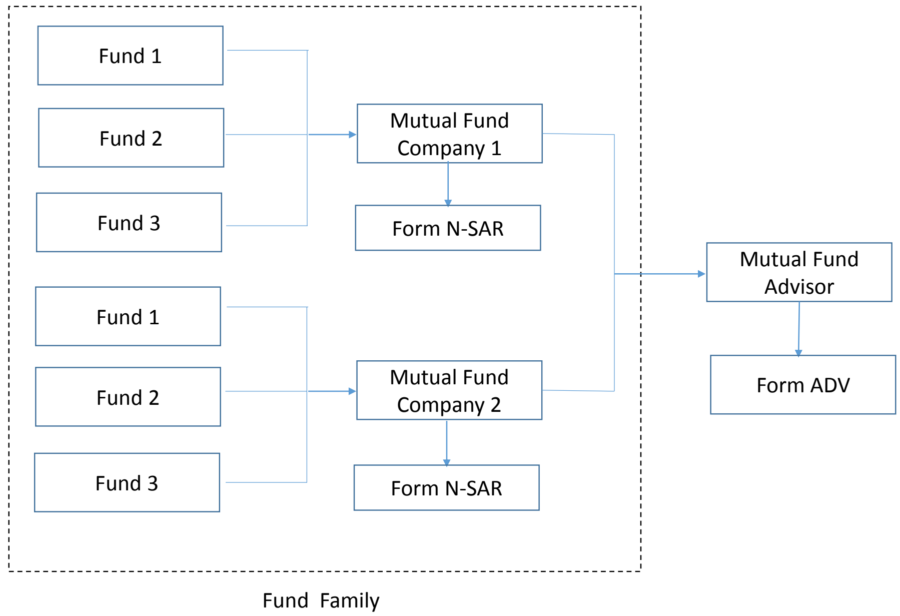


Figure 2.1: Organization Structure of Mutual Fund Advisory Business

This figure shows a typical organization structure of mutual fund advisory business. Note that mutual fund advisor may provide portfolio management for single or multiple mutual fund companies.

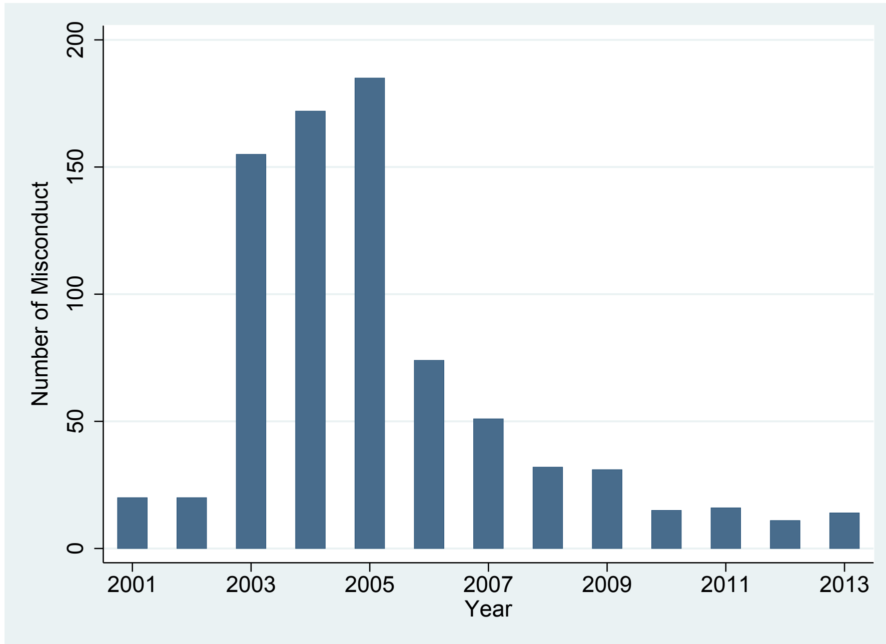
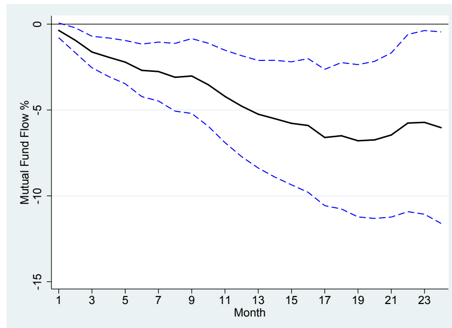
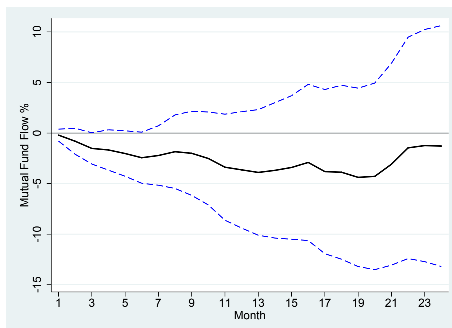


Figure 2.2: Mutual Fund Advisory Misconduct Cases Over Time

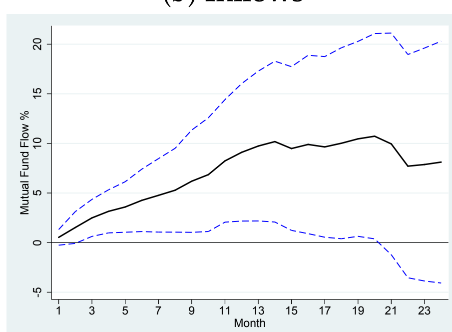
This figure reports time-series frequency of mutual fund advisory misconduct cases from 2001 to 2013 by case initiation date. The mutual fund advisory misconduct is defined as malfeasant behaviors on mutual funds that leads to disciplinary actions from regulatory agencies. The detailed misconduct information is obtained from the Regulatory Disclosure Reporting Page of Form ADV.



(a) **Netflows**



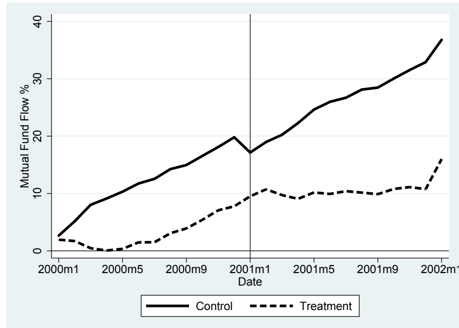
(b) **Inflows**



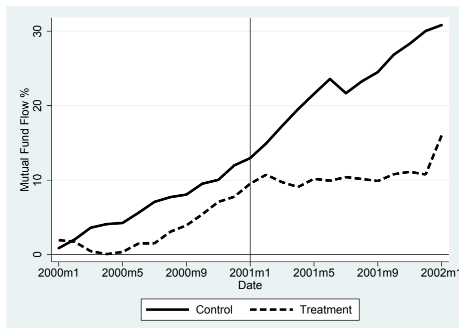
(c) **Outflows**

Figure 2.3: Effect of Mutual Fund Advisory Misconduct on Flows

This figure reports the coefficient estimates of *Mutual Fund Misconduct Dummy* (solid) and the 95% confidence interval (dash) in Table 2.3 from month t=1 to 24, where month t=0 denotes the time when mutual fund advisory misconduct case occurs. Panel A-Panel C shows result for netflows, inflows and outflows, respectively.



(a) **Unmatched Sample**



(b) **Matched Sample**

(c) **Treatment Effect**

Figure 2.4: Advisors' Cumulative Aggregate Flows Around The Mandate

This figure shows cumulative average advisors' aggregate netflows around the SEC electronic filing mandate effective in January 2001. The treatment group is defined as advisors with at least one mutual fund advisory misconduct case reported in the Form ADV as of January 2001, while control group includes advisors without any mutual fund advisory misconduct case as of the same point in time. Panel A plots cumulative average advisors' aggregate netflows for the unmatched sample, Panel B plots cumulative average advisors' aggregate netflows for the matched sample, and Panel C plots coefficient estimates (solid) and the 95% confidence interval (dash) of interaction terms $Month_t \times Treatment_{i,t}$ in the following regression:

$$Flows_{i,t} = \alpha + \delta Treatment_{i,t} + \sum_{t=-12}^{12} \{\beta_t Month_t \times Treatment_{i,t} + \gamma_t Month_t\} + \epsilon_{i,t}$$

where $Flows_{i,t}$ is cumulative aggregate netflows of advisor i from month t =-12 up to month t. Event date t=0 is set to be the base period and thus is omitted. The regression is estimated based on the matched sample. Standard errors are clustered by advisor and month.

Table 2.1: Summary Statistics

This table reports summary statistics for the variables from 2000 to 2013. Annual N-SAR filings of all mutual funds are matched with Form ADV based on SEC number and advisor name. *Netflow* is monthly total NAV of shares sold less total NAV of shares redeemed (N-SAR Item 28), scaled by total net assets (N-SAR Item 75). *Inflow* is monthly total NAV of shares sold scaled by total net assets, and *Outflow* is monthly total NAV of shares redeemed scaled by total net assets. *Return* is annual mutual fund return calculated using NAV and distributions. *Mutual Fund Misconduct Dummy* equals one if an advisor commits at least one mutual fund advisory misconduct case in month t, and zero otherwise. *Ln(Fund TNA)* is log of fund's total net assets. *Ln(Fund Age)* is log of years since fund's inception in N-SAR. *Expense Ratio* is the percentage of total expenses (N-SAR Item 72-X) over total net assets. *Front-End Load* is percentage of total front-end sales loads collected from sales over total net assets. *Redemption Fee* is percentage of total amount deferred or contingent deferred sales loads and redemption fees over total net assets. *Ln(Fund Family TNA)* is log of total net assets of fund family, where fund family identifiers are obtained from N-SAR Item 19. Investment style variables in Panel A are dummy variables corresponding to each investment style, while in Panel B they are percentage of fund net assets belonging to certain investment style in aggregate net assets managed by an advisor. Detailed variable definitions are shown in the Appendix A.8.

Panel A: Fund Level								
	N	Mean	S.D.	Q10	Q25	Median	Q75	Q90
Netflow %	1176555	0.79	7.72	-3.01	-1.14	0.00	1.38	5.08
Inflow %	1176555	6.55	16.18	0.00	0.53	1.72	4.55	14.45
Outflow %	1176555	5.89	14.85	0.00	0.81	1.77	3.53	11.36
Return %	721024	2.74	24.50	-24.83	-4.77	1.88	13.53	28.12
Mutual Fund Misconduct Dummy	1176555	0.01	0.09	0.00	0.00	0.00	0.00	0.00
Fund TNA (Billion $)	1161735	1.28	5.04	0.02	0.06	0.21	0.74	2.36
Fund Age	1176555	5.16	4.15	1.00	2.00	4.00	7.00	11.00
Expense Ratio %	1155263	1.17	1.07	0.27	0.60	0.95	1.39	2.09
Front-End Load %	1155263	0.04	0.12	0.00	0.00	0.00	0.00	0.10
Redemption Fee %	1155263	0.01	0.03	0.00	0.00	0.00	0.00	0.02
Fund Family TNA (Billion $)	1172200	145.86	315.90	0.11	2.93	34.35	115.88	318.08
Domestic Bond	1176555	0.31	0.46	0.00	0.00	0.00	1.00	1.00
Equity-Capital Appr'n	1176555	0.11	0.32	0.00	0.00	0.00	0.00	1.00
Equity-Growth and Income	1176555	0.10	0.30	0.00	0.00	0.00	0.00	1.00
Equity-Total Return %	1176555	0.04	0.19	0.00	0.00	0.00	0.00	0.00
Balanced	1176555	0.04	0.19	0.00	0.00	0.00	0.00	0.00
Equity Index	1176555	0.09	0.29	0.00	0.00	0.00	0.00	0.00
Bond Index	1176555	0.01	0.12	0.00	0.00	0.00	0.00	0.00
Foreign Equity	1176555	0.06	0.24	0.00	0.00	0.00	0.00	0.00
Foreign Bond	1176555	0.01	0.08	0.00	0.00	0.00	0.00	0.00
Others	1176555	0.22	0.41	0.00	0.00	0.00	0.00	1.00
Panel B: Advisor Level								
	N	Mean	S.D.	Q10	Q25	Median	Q75	Q90
Netflow %	92398	0.71	5.02	-2.22	-0.68	0.00	1.12	3.69
Inflow %	92398	6.59	13.79	0.00	0.56	2.18	5.38	16.14
Outflow %	92398	5.92	12.76	0.00	0.69	1.96	4.24	14.30
Return %	75592	2.69	21.23	-22.64	-5.73	3.46	13.04	24.04
Mutual Fund Misconduct Dummy	92398	0.00	0.05	0.00	0.00	0.00	0.00	0.00
Total TNA (Billion $)	92398	20.34	84.16	0.02	0.10	0.83	6.86	40.91
Total Employees (1,000)	92206	0.22	1.08	0.00	0.01	0.03	0.15	0.38
Total Clients (1,000)	91973	3.18	29.36	0.01	0.01	0.06	0.38	2.00
Total Accounts (1,000)	92046	19.79	1461.58	0.00	0.01	0.07	0.45	2.66
Firm Branches	92398	2.63	15.35	1.00	1.00	1.00	2.00	5.00
Firm Age	92398	6.89	3.78	2.00	4.00	7.00	10.00	12.00
Domestic Bond	92398	0.22	0.32	0.00	0.00	0.00	0.35	0.83
Equity-Capital Appr'n	92398	0.24	0.37	0.00	0.00	0.00	0.37	1.00
Equity-Growth and Income	92398	0.18	0.33	0.00	0.00	0.00	0.18	0.93
Equity-Total Return	92398	0.06	0.21	0.00	0.00	0.00	0.00	0.12
Balanced	92398	0.04	0.13	0.00	0.00	0.00	0.00	0.08
Equity Index	92398	0.09	0.23	0.00	0.00	0.00	0.05	0.27
Bond Index	92398	0.01	0.06	0.00	0.00	0.00	0.00	0.00
Foreign Equity	92398	0.03	0.13	0.00	0.00	0.00	0.00	0.04
Foreign Bond	92398	0.00	0.02	0.00	0.00	0.00	0.00	0.00
Others	92398	0.12	0.23	0.00	0.00	0.00	0.13	0.45

Table 2.2: Predicting Mutual Fund Advisory Misconduct

This table provides result of linear probability and Logit model for predicting mutual fund advisory misconduct. The sample consists of advisor-year observations from 2000 to 2013. The dependent variable is an indicator equals to one if an advisor commits at least one mutual fund advisory misconduct case in year $t+1$. The explanatory variables include *Past Mutual Fund Misconduct*, a dummy variable equals one if an advisor commits at least one mutual fund advisory misconduct in year t; *Past Affiliated Mutual Fund Misconduct*, a dummy variable equals one if the mutual fund advisory misconduct is committed by an advisor affiliate in year t; *Past Regulatory*, a dummy variable equals one if an advisor files a regulatory disclosure reporting page (DRP) in year t; *Past Civil or Criminal*, a dummy variable equals one if an advisor files a criminal or civil DRP in year t; *Regional Misconduct Intensity*, defined as total number of historical mutual fund advisory misconduct as of year t scaled by the population in a Zipcode region. Detailed definitions of other control variables are provided in Appendix A.8. Both models include year fixed effects, and report original coefficient estimates. The R^2 for LPM is adjusted R^2, while the R^2 for Logit model is pseudo R^2. The robust t-statistics clustered by advisor are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	LPM		Logit	
	(1)	(2)	(3)	(4)
Past Mutual Fund Misconduct	0.0225	0.0138	0.4123	0.4667
	(0.660)	(0.379)	(0.772)	(0.714)
Past Affiliated Mutual Fund Misconduct	-0.0364	-0.0421	-0.7463	-1.2452
	(-0.717)	(-0.682)	(-0.643)	(-0.660)
Past Regulatory	0.0338***	0.0340***	1.8696***	1.8234***
	(4.884)	(4.483)	(5.512)	(5.263)
Past Civil or Criminal	0.0332***	0.0349**	0.7613***	0.8903***
	(2.701)	(2.551)	(2.745)	(3.121)
Regional Misconduct Intensity		0.0149**		0.1532
		(2.281)		(1.132)
Lagged Returns	0.0051	0.0093	0.4946	0.8086
	(0.522)	(0.885)	(0.637)	(1.045)
Lagged Flows	-0.0215	-0.0194	-1.3966	-1.4386
	(-0.547)	(-0.476)	(-0.654)	(-0.620)
Interest in Transaction	-0.0007	-0.0007	0.0351	0.0007
	(-0.181)	(-0.178)	(0.103)	(0.002)
Referral Fees	0.0011	0.0024	0.2134	0.3329
	(0.248)	(0.532)	(0.685)	(1.019)
Soft Dollars	0.0007	0.0010	0.0725	0.0507
	(0.177)	(0.233)	(0.153)	(0.106)
Broker in Firm	0.0022	0.0035	0.6354	0.7658
	(0.720)	(1.138)	(1.416)	(1.566)
Custody	0.0071	0.0081	0.2962	0.3780
	(1.093)	(1.220)	(0.947)	(1.106)
Ln(Total AUM)	0.0035**	0.0027*	0.2253***	0.2043**
	(2.224)	(1.758)	(2.649)	(2.406)
Ln(Avg. Acc. Size)	-0.0020	-0.0016	-0.0635	-0.0484
	(-1.144)	(-0.894)	(-0.833)	(-0.616)
Percent Client Agents	0.0001	0.0001	0.0071	0.0072
	(1.422)	(1.220)	(1.313)	(1.273)
Ln(Firm Age)	-0.0062	-0.0055	-0.4063	-0.2708
	(-1.052)	(-0.875)	(-0.819)	(-0.445)
Avg. Flows to Fund Style	-0.0453	-0.0271	-1.2348	-0.0629
	(-1.291)	(-0.754)	(-0.659)	(-0.033)
Year FE	Y	Y	Y	Y
Observations	4598	4178	4598	4178
Number of Advisors	786	732	786	732
R^2	0.04	0.04	0.22	0.23

Table 2.3: Mutual Fund Advisory Misconduct and Advisors' Aggregate Flows

This table provides panel regression result of advisors' cumulative monthly aggregate flows on mutual fund advisory misconduct. The sample consists of advisor-month observations from 2000 to 2013. The dependent variable in Panel A is cumulative aggregate advisors' netflows from month t up to month $t+n$ (n=1,2,3,6,12,18,24), where the aggregate advisors' netflows are defined as the gross netflows over gross TNA of mutual funds managed by a particular advisor. The dependent variable in Panel B and C is inflows and outflows, respectively. The main explanatory variable *Mutual Fund Misconduct Dummy* equals one if an advisor commits at least one mutual fund advisory misconduct case in month t, and zero otherwise. *Ln(Past Monetary Fine)* is log of monetary fine associated with all misconduct of an advisor as of month t. *Lagged Returns* is TNA-weighted average returns of all funds managed by an advisor in last year. *Lagged Flows* is aggregate netflows of an advisor in month t. Detailed variable definitions are provided in Appendix A.8. All regressions include month fixed effects. The robust t-statistics clustered by advisor and month are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Netflows							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	t+1	(t+1,t+2)	(t+1,t+3)	(t+1,t+6)	(t+1,t+12)	(t+1,t+18)	(t+1,t+24)
Mutual Fund Misconduct Dummy	-0.0036*	-0.0094**	-0.0162***	-0.0269***	-0.0477***	-0.0650***	-0.0603**
	(-1.67)	(-2.55)	(-3.49)	(-3.47)	(-3.21)	(-3.01)	(-2.14)
Ln(Past Monetary Fine)	-0.0001	-0.0001	-0.0002	-0.0005	-0.0010	-0.0015	-0.0025
	(-0.94)	(-1.01)	(-1.03)	(-1.11)	(-1.02)	(-0.93)	(-1.05)
Lagged Returns	0.0021	0.0046	0.0073	0.0181*	0.0341	0.0212	0.0149
	(1.36)	(1.46)	(1.49)	(1.69)	(1.52)	(0.66)	(0.34)
Lagged Flows	0.4859***	0.9145***	1.3220***	2.3851***	4.3020***	6.0046***	7.5396***
	(8.12)	(7.27)	(6.81)	(5.68)	(4.64)	(4.10)	(3.72)
Expense Ratio	-0.0011***	-0.0024***	-0.0036***	-0.0071***	-0.0120**	-0.0186**	-0.0283**
	(-4.04)	(-4.16)	(-4.16)	(-3.67)	(-2.27)	(-2.42)	(-2.56)
Front-End Load	0.0061**	0.0123*	0.0180*	0.0328	0.0572	0.0680	0.0704
	(2.03)	(1.93)	(1.84)	(1.57)	(1.20)	(0.91)	(0.71)
Redemption Fee	0.0140	0.0275	0.0354	0.0403	-0.0087	0.0094	-0.1316
	(1.05)	(0.96)	(0.79)	(0.42)	(-0.04)	(0.03)	(-0.31)
Ln(Total AUM)	-0.0001	-0.0001	-0.0003	-0.0003	-0.0002	-0.0002	0.0006
	(-0.30)	(-0.35)	(-0.38)	(-0.22)	(-0.06)	(-0.03)	(0.07)
Ln(Firm Age)	-0.0045***	-0.0094***	-0.0149***	-0.0309***	-0.0648***	-0.1003***	-0.1329***
	(-3.78)	(-3.66)	(-3.72)	(-3.65)	(-3.28)	(-3.53)	(-3.41)
Avg. Flows to Fund Style	0.1491***	0.2985**	0.4180**	0.5973	0.9902	0.9754	0.4198
	(2.61)	(2.50)	(2.28)	(1.54)	(1.11)	(0.70)	(0.21)
Month FE	Y	Y	Y	Y	Y	Y	Y
Observations	74236	73130	72032	68808	62573	57232	52062
Number of Advisors	1023	1021	1012	1000	872	857	759
Adjusted R^2	0.25	0.29	0.31	0.32	0.30	0.29	0.28

Panel B: Inflows							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	t+1	(t+1,t+2)	(t+1,t+3)	(t+1,t+6)	(t+1,t+12)	(t+1,t+18)	(t+1,t+24)
Mutual Fund Misconduct Dummy	-0.0020	-0.0081	-0.0152*	-0.0244*	-0.0364	-0.0388	-0.0129
	(-0.68)	(-1.24)	(-1.94)	(-1.91)	(-1.25)	(-0.89)	(-0.21)
Ln(Past Monetary Fine)	-0.0000	-0.0001	-0.0003	-0.0007	-0.0015	-0.0026	-0.0043
	(-0.57)	(-0.84)	(-0.94)	(-1.11)	(-1.05)	(-1.17)	(-1.35)
Lagged Returns	0.0007	0.0025	0.0050	0.0150	0.0350	0.0240	0.0288
	(0.32)	(0.53)	(0.66)	(0.90)	(1.13)	(0.51)	(0.43)
Lagged Flows	0.4742***	0.7776***	1.0169***	1.4862***	2.3227***	2.9280***	3.3241**
	(11.68)	(7.89)	(6.35)	(4.39)	(3.35)	(2.81)	(2.44)
Expense Ratio	-0.0015***	-0.0034***	-0.0053***	-0.0104***	-0.0165**	-0.0247**	-0.0361**
	(-4.54)	(-4.34)	(-4.25)	(-3.65)	(-2.30)	(-2.38)	(-2.45)
Front-End Load	0.0069**	0.0164**	0.0271**	0.0573**	0.1095*	0.1510	0.1852
	(2.20)	(2.23)	(2.28)	(2.13)	(1.77)	(1.58)	(1.47)
Redemption Fee	0.0127	0.0288	0.0409	0.0571	0.0032	0.0236	-0.1023
	(0.98)	(0.93)	(0.81)	(0.50)	(0.01)	(0.06)	(-0.19)
Ln(Total AUM)	-0.0000	-0.0002	-0.0006	-0.0015	-0.0029	-0.0038	-0.0039
	(-0.09)	(-0.44)	(-0.64)	(-0.69)	(-0.58)	(-0.45)	(-0.31)
Ln(Firm Age)	-0.0047***	-0.0108***	-0.0180***	-0.0402***	-0.0890***	-0.1320***	-0.1639***
	(-3.39)	(-3.34)	(-3.42)	(-3.44)	(-3.10)	(-3.45)	(-3.23)
Avg. Flows to Fund Style	0.2710***	0.5774***	0.8820***	1.5656***	2.5287**	2.8908*	2.4415
	(4.74)	(4.44)	(4.16)	(3.32)	(2.29)	(1.67)	(1.02)
Contemporaneous Outflows	0.5266***	0.6210***	0.6771***	0.7771***	0.8365***	0.8690***	0.8958***
	(12.92)	(12.31)	(12.23)	(13.09)	(13.71)	(14.16)	(14.98)
Month FE	Y	Y	Y	Y	Y	Y	Y
Observations	74236	73130	72032	68808	62573	57232	52062
Number of Advisors	1023	1021	1012	1000	872	857	759
Adjusted R^2	0.88	0.91	0.92	0.93	0.94	0.95	0.95

Panel C: Outflows							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	t+1	(t+1,t+2)	(t+1,t+3)	(t+1,t+6)	(t+1,t+12)	(t+1,t+18)	(t+1,t+24)
Mutual Fund Misconduct Dummy	0.0053	0.0152*	0.0249***	0.0426***	0.0910**	0.1002**	0.0811
	(1.33)	(1.88)	(2.64)	(2.67)	(2.60)	(2.06)	(1.32)
Ln(Past Monetary Fine)	0.0002**	0.0003**	0.0005**	0.0012**	0.0026*	0.0043*	0.0065*
	(2.08)	(2.03)	(1.99)	(2.09)	(1.88)	(1.87)	(1.88)
Lagged Returns	-0.0039**	-0.0087**	-0.0142**	-0.0334**	-0.0674**	-0.0762*	-0.0900
	(-2.03)	(-2.04)	(-2.14)	(-2.48)	(-2.53)	(-1.92)	(-1.61)
Lagged Flows	0.4477***	0.7809***	1.0867***	1.8073***	2.9985***	3.8810***	4.5497***
	(12.44)	(9.06)	(7.68)	(5.85)	(4.56)	(3.90)	(3.50)
Expense Ratio	0.0009***	0.0020***	0.0033***	0.0067***	0.0105*	0.0152*	0.0224*
	(2.64)	(2.64)	(2.80)	(2.63)	(1.76)	(1.73)	(1.79)
Front-End Load	-0.0117***	-0.0237***	-0.0364***	-0.0732***	-0.1490***	-0.2078***	-0.2493**
	(-3.84)	(-3.40)	(-3.46)	(-3.26)	(-2.99)	(-2.69)	(-2.43)
Redemption Fee	-0.0217*	-0.0449*	-0.0664	-0.1044	-0.1605	-0.2413	-0.2435
	(-1.87)	(-1.72)	(-1.63)	(-1.17)	(-0.82)	(-0.81)	(-0.62)
Ln(Total AUM)	0.0006***	0.0012***	0.0019***	0.0038**	0.0079**	0.0119**	0.0158**
	(2.66)	(2.63)	(2.62)	(2.43)	(2.29)	(2.20)	(2.04)
Ln(Firm Age)	0.0047***	0.0097***	0.0155***	0.0338***	0.0739***	0.1097***	0.1370***
	(3.53)	(3.27)	(3.34)	(3.33)	(3.04)	(3.28)	(3.03)
Avg. Flows to Fund Style	-0.2586***	-0.5610***	-0.8506***	-1.5472***	-2.8672***	-3.9189**	-4.4379**
	(-3.86)	(-4.09)	(-4.10)	(-3.49)	(-2.81)	(-2.48)	(-2.07)
Contemporaneous Inflows	0.4878***	0.5426***	0.5708***	0.6310***	0.6812***	0.7138***	0.7398***
	(12.89)	(11.86)	(11.34)	(11.25)	(11.09)	(11.19)	(11.56)
Month FE	Y	Y	Y	Y	Y	Y	Y
Observations	74236	73130	72032	68808	62573	57232	52062
Number of Advisors	1023	1021	1012	1000	872	857	759
Adjusted R^2	0.88	0.91	0.93	0.94	0.95	0.95	0.95

Table 2.4: Aggregate Fund Flows Around The SEC Electronic Filing Mandate

This table provides estimate of cumulative treatment effect for the SEC electronic filing mandate. The sample consists of advisor-month observations from 2000-2001. The dependent variable is advisors' cumulative aggregate netflows from month $t = -12$ up to month t. The main explanatory variables *Treatment*Qtr* is interaction terms between *Treatment*, a dummy variable equals one for an advisor with at least one mutual fund advisory misconduct case in Form ADV as of January 2001, and zero otherwise; and a series of quarter dummies from quarter -4 to +4. The Panel A reports result for the unmatched sample, while Panel B reports result for the matched sample, where each treatment advisor is matched to multiple control advisors based on assets under management. Panel C reports result for testing covariates balance before and after the match. Panel D reports result of a placebo test for the matched sample in which the event date is set to be January 1998. All regressions include quarter dummy variables. The additional controls include log of advisor's total AUM, log of firm age, log of past monetary fine, average fund returns and average flows to fund style, and are not reported. Detailed variable definitions are provided in Appendix A.8. The robust t-statistics clustered by advisor and month are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Unmatched Sample

	Netflow		Inflow		Outflow	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-0.0763*	-0.1706*	1.2425**	0.8205*	1.3119***	0.9142*
	(-1.96)	(-1.79)	(2.65)	(1.75)	(2.90)	(2.03)
Treatment*Qtr(-4,-3)	0.0371	0.2033**	-0.9823***	-0.7324**	-1.0222***	-0.8774**
	(1.53)	(2.24)	(-2.82)	(-2.13)	(-2.95)	(-2.56)
Treatment*Qtr(-3,-2)	-0.0214	0.1639*	-0.6142***	-0.2875	-0.5969***	-0.3980*
	(-1.03)	(1.92)	(-3.41)	(-1.27)	(-3.37)	(-1.80)
Treatment*Qtr(-2,-1)	-0.0346**	0.1451*	-0.3266***	0.0040	-0.2955***	-0.0877
	(-2.39)	(1.86)	(-5.28)	(0.03)	(-4.60)	(-0.57)
Treatment*Qtr(-1,0)	-0.0377***	0.1427*	-0.1263***	0.2261*	-0.0932***	0.1338
	(-3.06)	(1.93)	(-3.45)	(1.91)	(-2.91)	(1.11)
Treatment*Qtr(0,+1)	-0.0302***	-0.0251	0.1391	0.1045	0.1711	0.1340
	(-2.93)	(-1.26)	(1.10)	(0.71)	(1.39)	(0.95)
Treatment*Qtr(+1,+2)	-0.0796***	-0.0567**	0.3520*	0.3367	0.4293**	0.3959*
	(-4.09)	(-2.40)	(1.88)	(1.70)	(2.34)	(2.04)
Treatment*Qtr(+2,+3)	-0.1096***	-0.0926***	0.5019**	0.4404*	0.6060**	0.5341**
	(-4.39)	(-3.39)	(2.16)	(1.86)	(2.64)	(2.26)
Treatment*Qtr(+3,+4)	-0.1341***	-0.1037***	0.7561**	0.7703**	0.8744***	0.8681***
	(-5.29)	(-3.96)	(2.64)	(2.62)	(3.09)	(2.97)
Quarter Dummies	Y	Y	Y	Y	Y	Y
Additional Controls	N	Y	N	Y	N	Y
Observations	12473	9859	12473	9859	12473	9859
Number of Advisors	598	537	598	537	598	537
Adjusted R^2	0.03	0.07	0.08	0.14	0.07	0.14

Panel B: Matched Sample						
	Netflow		Inflow		Outflow	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-0.0344	0.0398	1.0693**	0.7457	1.0756**	0.6859
	(-0.68)	(0.70)	(2.18)	(1.65)	(2.27)	(1.59)
Treatment*Qtr(-4,-3)	0.0265	0.0241	-0.8397**	-0.4580	-0.8455**	-0.4530
	(0.79)	(0.52)	(-2.31)	(-1.27)	(-2.34)	(-1.28)
Treatment*Qtr(-3,-2)	-0.0057	0.0083	-0.5038**	-0.0555	-0.4824**	-0.0429
	(-0.21)	(0.19)	(-2.63)	(-0.20)	(-2.58)	(-0.16)
Treatment*Qtr(-2,-1)	-0.0134	-0.0073	-0.2516***	0.2313	-0.2305***	0.2460
	(-0.60)	(-0.20)	(-3.79)	(0.94)	(-3.37)	(1.00)
Treatment*Qtr(-1,0)	-0.0032	0.0042	-0.0789*	0.4336	-0.0780**	0.4251
	(-0.16)	(0.12)	(-2.06)	(1.70)	(-2.32)	(1.66)
Treatment*Qtr(0,+1)	-0.0396***	-0.0308	0.0910	0.1023	0.1174	0.1209
	(-3.24)	(-1.10)	(0.70)	(0.58)	(0.92)	(0.71)
Treatment*Qtr(+1,+2)	-0.0867***	-0.0563*	0.2492	0.2486	0.3030	0.2788
	(-2.92)	(-1.81)	(1.27)	(1.17)	(1.57)	(1.33)
Treatment*Qtr(+2,+3)	-0.1116**	-0.0566**	0.3826	0.3700	0.4636*	0.4113
	(-2.53)	(-2.12)	(1.56)	(1.50)	(1.91)	(1.68)
Treatment*Qtr(+3,+4)	-0.1369**	-0.0930***	0.5603*	0.5668*	0.6531**	0.6300**
	(-2.58)	(-3.92)	(1.85)	(1.96)	(2.18)	(2.18)
Quarter Dummies	Y	Y	Y	Y	Y	Y
Additional Controls	N	Y	N	Y	N	Y
Observations	2124	1897	2124	1897	2124	1897
Number of Advisors	97	94	97	94	97	94
Adjusted R^2	0.03	0.12	0.15	0.21	0.15	0.21

Panel C: Balance Test of Covariates					
	Sample	Control	Treatment	Diff	T-stats
Ln(Total AUM)	Full	21.08	23.99	-2.91	-6.79
	Matched	23.82	23.99	-0.17	-0.37
Ln(Total Employees)	Full	3.35	5.10	-1.75	-3.47
	Matched	4.96	5.10	-0.13	-0.24
Ln(Total Clients)	Full	4.15	5.74	-1.59	-2.63
	Matched	5.17	5.74	-0.56	-0.86
Ln(Total Accounts)	Full	4.07	5.50	-1.43	-2.22
	Matched	5.36	5.50	-0.13	-0.19
Ln(Firm Branches)	Full	0.35	0.87	-0.52	-1.58
	Matched	0.73	0.87	-0.14	-0.41
Ln(Firm Age)	Full	0.64	0.71	-0.08	-3.39
	Matched	0.66	0.71	-0.05	-1.68
Expense Ratio	Full	1.62	0.91	0.71	6.24
	Matched	1.05	0.91	0.14	0.90
Front-End Load	Full	0.04	0.02	0.02	1.87
	Matched	0.02	0.02	0.01	0.46
Redemption Fee	Full	0.01	0.01	-0.00	-0.32
	Matched	0.01	0.01	-0.00	-0.75

Panel D: Placebo Test						
	Netflow		Inflow		Outflow	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.0917	0.1188	0.5306	0.6275	0.3698	0.4355
	(0.57)	(0.76)	(1.08)	(1.29)	(0.86)	(1.04)
Treatment*Qtr(-4,-3)	-0.0212	-0.0716	-0.2268	-0.4430	-0.2031	-0.3019
	(-0.30)	(-0.67)	(-0.63)	(-0.95)	(-0.65)	(-0.77)
Treatment*Qtr(-3,-2)	0.0203	-0.0319	-0.0038	-0.3470	-0.0396	-0.2484
	(0.91)	(-0.35)	(-0.01)	(-0.85)	(-0.19)	(-0.78)
Treatment*Qtr(-2,-1)	0.0630*	-0.0247	0.2114	-0.2564	0.1261	-0.1656
	(1.87)	(-0.28)	(0.80)	(-0.70)	(0.64)	(-0.65)
Treatment*Qtr(-1,0)	0.0732	0.0141	0.3526	0.0650	0.2503	0.0685
	(1.49)	(0.25)	(1.23)	(0.22)	(1.12)	(0.36)
Treatment*Qtr(0,+1)	0.0621	0.0877	0.6430*	0.6606	0.5303	0.4906
	(0.81)	(0.82)	(1.75)	(1.53)	(1.64)	(1.29)
Treatment*Qtr(+1,+2)	0.0558	0.0811	0.8536*	0.8195	0.7366*	0.6362
	(0.66)	(0.71)	(1.96)	(1.59)	(1.81)	(1.32)
Treatment*Qtr(+2,+3)	0.0715	0.0923	0.9662*	0.9493	0.8250*	0.7424
	(0.85)	(0.78)	(1.99)	(1.65)	(1.78)	(1.35)
Treatment*Qtr(+3,+4)	0.0924	0.1070	1.1033**	1.0036*	0.9413*	0.8004
	(1.16)	(1.07)	(2.30)	(1.88)	(2.04)	(1.56)
Quarter Dummies	Y	Y	Y	Y	Y	Y
Additional Controls	N	Y	N	Y	N	Y
Observations	2043	1709	2043	1709	2043	1709
Number of Advisors	88	81	88	81	88	81
Adjusted R^2	0.05	0.13	0.15	0.27	0.12	0.22

Table 2.5: Robustness Checks: Excluding 2003-2005 Market Timing/Late Trading Scandals

This table provides regression result of advisors' cumulative monthly aggregate flows on mutual fund advisory misconduct. The sample consists of advisor-month observations from 2000 to 2013, excluding 2003-2005 episode of market timing and late trading scandals. The dependent variable is cumulative aggregate advisors' netflows from month t up to month $t+n$ (n=1,2,3,6,12,18,24), where the aggregate advisors' netflows are defined as the gross netflows over gross TNA of mutual funds managed by a particular advisor. The main explanatory variable *Mutual Fund Misconduct Dummy* equals one if an advisor commits at least one mutual fund advisory misconduct case in month t, and zero otherwise. *Ln(Past Monetary Fine)* is log of monetary fine associated with all misconduct of an advisor as of month t. *Lagged Returns* is TNA-weighted average returns of all funds managed by an advisor in last year. *Lagged Flows* is aggregate netflows of an advisor in month t. Detailed definitions of other control variables are provided in Appendix A.8. All regressions include month fixed effects. The robust t-statistics clustered by advisor and month are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	t+1	(t+1,t+2)	(t+1,t+3)	(t+1,t+6)	(t+1,t+12)	(t+1,t+18)	(t+1,t+24)
Mutual Fund Misconduct Dummy	-0.0025	-0.0078*	-0.0149***	-0.0217***	-0.0390**	-0.0483**	-0.0301
	(-0.98)	(-1.89)	(-2.88)	(-2.73)	(-2.42)	(-2.15)	(-1.09)
Ln(Past Monetary Fine)	-0.0000	-0.0001	-0.0001	-0.0003	-0.0006	-0.0008	-0.0017
	(-0.45)	(-0.48)	(-0.53)	(-0.64)	(-0.55)	(-0.51)	(-0.73)
Lagged Returns	0.0018	0.0042	0.0068	0.0174	0.0390*	0.0358	0.0417
	(1.16)	(1.30)	(1.32)	(1.58)	(1.78)	(1.23)	(1.10)
Lagged Flows	0.4829***	0.8986***	1.2849***	2.2604***	3.9750***	5.3818***	6.5437***
	(9.36)	(8.31)	(7.69)	(6.28)	(5.01)	(4.33)	(3.83)
Expense Ratio	-0.0013***	-0.0027***	-0.0042***	-0.0086***	-0.0152***	-0.0204***	-0.0254**
	(-4.96)	(-5.08)	(-4.99)	(-4.60)	(-3.41)	(-2.81)	(-2.34)
Front-End Load	0.0046	0.0089	0.0125	0.0202	0.0282	0.0237	0.0187
	(1.52)	(1.36)	(1.25)	(0.92)	(0.57)	(0.31)	(0.19)
Redemption Fee	0.0128	0.0257	0.0374	0.0599	0.0846	0.1854	0.0367
	(1.01)	(0.93)	(0.87)	(0.63)	(0.39)	(0.54)	(0.08)
Ln(Total AUM)	-0.0001	-0.0003	-0.0005	-0.0010	-0.0025	-0.0045	-0.0062
	(-0.58)	(-0.70)	(-0.76)	(-0.68)	(-0.79)	(-0.86)	(-0.80)
Ln(Firm Age)	-0.0047***	-0.0099***	-0.0159***	-0.0341***	-0.0733***	-0.1105***	-0.1395***
	(-3.81)	(-3.68)	(-3.76)	(-3.76)	(-3.44)	(-3.59)	(-3.29)
Avg. Flows to Fund Style	0.1371***	0.2830**	0.3895**	0.5058	0.8490	0.8420	0.6223
	(2.66)	(2.60)	(2.33)	(1.42)	(1.03)	(0.67)	(0.36)
Month FE	Y	Y	Y	Y	Y	Y	Y
Observations	57799	56854	55916	53169	47820	43282	38881
Number of Advisors	986	984	974	963	838	824	732
Adjusted R^2	0.24	0.29	0.30	0.30	0.28	0.26	0.25

Table 2.6: Robustness Checks: Quarterly Flows

This table provides regression result of advisors' cumulative quarterly aggregate flows on mutual fund advisory misconduct. The sample consists of advisor-quarter observations from 2000 to 2013. The dependent variable is cumulative aggregate advisors' netflows from quarter t up to quarter $t+n$ (n=1,2,3,4,6,8), where the aggregate advisors' netflows are defined as the gross netflows over gross TNA of mutual funds managed by a particular advisor. The main explanatory variable *Mutual Fund Misconduct Dummy* equals one if an advisor commits at least one mutual fund advisory misconduct case in quarter t, and zero otherwise. *Ln(Past Monetary Fine)* is log of monetary fine associated with all misconduct of an advisor as of quarter t. *Lagged Returns* is TNA-weighted average returns of all funds managed by an advisor in last year. *Lagged Flows* is aggregate netflows of an advisor in quarter t. Detailed definitions of other control variables are provided in Appendix A.8. All regressions include quarter fixed effects. The robust t-statistics clustered by advisor and quarter are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	t+1	(t+1,t+2)	(t+1,t+3)	(t+1,t+4)	(t+1,t+6)	(t+1,t+8)
Mutual Fund Misconduct Dummy	-0.0039	-0.0079**	-0.0173***	-0.0203***	-0.0242***	-0.0288**
	(-1.56)	(-2.31)	(-4.34)	(-3.49)	(-3.24)	(-2.63)
Ln(Past Monetary Fine)	-0.0001	-0.0002	-0.0002	-0.0003	-0.0004	-0.0007
	(-0.88)	(-1.06)	(-0.94)	(-0.85)	(-0.70)	(-0.86)
Lagged Returns	0.0033*	0.0068*	0.0087	0.0100	0.0055	0.0077
	(1.89)	(1.71)	(1.49)	(1.24)	(0.48)	(0.49)
Lagged Flows	0.4133***	0.7585***	1.0792***	1.4013***	1.9742***	2.5030***
	(5.78)	(5.07)	(4.62)	(4.37)	(3.94)	(3.63)
Expense Ratio	-0.0015***	-0.0029***	-0.0040***	-0.0049**	-0.0071**	-0.0091**
	(-3.46)	(-3.16)	(-2.79)	(-2.27)	(-2.35)	(-2.11)
Front-End Load	0.0048	0.0083	0.0137	0.0192	0.0240	0.0288
	(1.54)	(1.20)	(1.17)	(1.12)	(0.90)	(0.82)
Redemption Fee	0.0112	0.0135	0.0120	0.0078	0.0318	-0.0212
	(0.72)	(0.37)	(0.21)	(0.10)	(0.29)	(-0.14)
Ln(Total AUM)	-0.0002	-0.0004	-0.0005	-0.0007	-0.0010	-0.0008
	(-0.93)	(-0.66)	(-0.59)	(-0.52)	(-0.47)	(-0.27)
Ln(Firm Age)	-0.0066***	-0.0127***	-0.0196***	-0.0238***	-0.0356***	-0.0436***
	(-3.80)	(-3.93)	(-3.70)	(-3.24)	(-3.38)	(-2.83)
Avg. Flows to Fund Style	0.0827***	0.1244**	0.1726*	0.2387*	0.2414	0.2114
	(2.92)	(2.13)	(1.83)	(1.77)	(1.19)	(0.77)
Quarter FE	Y	Y	Y	Y	Y	Y
Observations	24124	23049	21995	20964	19185	17453
Number of Advisors	1014	1002	988	875	860	760
Adjusted R^2	0.19	0.22	0.23	0.24	0.25	0.24

Table 2.7: Robustness Checks: Omitted Variable Bias

This table provides regression result of advisors' cumulative monthly aggregate flows on mutual fund advisory misconduct with advisor fixed effects to address potential omitted variable bias. The sample consists of advisor-month observations from 2000 to 2013. The dependent variable is cumulative aggregate advisors' netflows from month t up to month $t + n$ (n=1,2,3,6,12,18,24), where the aggregate advisors' netflows are defined as the gross netflows over gross TNA of mutual funds managed by a particular advisor. The main explanatory variable *Mutual Fund Misconduct Dummy* equals one if an advisor commits at least one mutual fund advisory misconduct case in month t, and zero otherwise. *Ln(Past Monetary Fine)* is log of monetary fine associated with all misconduct of an advisor as of month t. *Lagged Returns* is TNA-weighted average returns of all funds managed by an advisor in last year. *Lagged Flows* is aggregate netflows of an advisor in month t. Detailed variable definitions are provided in Appendix A.8. All regressions include advisor and month fixed effects. The robust t-statistics clustered by advisor and month are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	t+1	(t+1,t+2)	(t+1,t+3)	(t+1,t+6)	(t+1,t+12)	(t+1,t+18)	(t+1,t+24)
Mutual Fund Misconduct Dummy	-0.0017	-0.0052	-0.0098**	-0.0134*	-0.0181	-0.0171	-0.0077
	(-0.79)	(-1.43)	(-2.13)	(-1.67)	(-1.14)	(-0.67)	(-0.21)
Ln(Past Monetary Fine)	0.0000	0.0001	0.0001	-0.0000	-0.0004	-0.0008	-0.0022
	(0.27)	(0.16)	(0.10)	(-0.03)	(-0.14)	(-0.16)	(-0.26)
Lagged Returns	0.0043***	0.0093***	0.0147***	0.0314***	0.0570**	0.0642**	0.0698*
	(3.14)	(3.02)	(3.00)	(2.83)	(2.43)	(2.06)	(1.71)
Lagged Flows	0.3638***	0.6545***	0.9176***	1.5134***	2.4133***	3.0437***	3.4313***
	(7.77)	(6.81)	(6.34)	(5.03)	(3.87)	(3.29)	(2.91)
Expense Ratio	0.0003	0.0008	0.0013	0.0029	0.0088	0.0176	0.0226
	(0.44)	(0.52)	(0.58)	(0.64)	(0.91)	(1.23)	(1.11)
Front-End Load	0.0093*	0.0190*	0.0276*	0.0518	0.0927	0.0931	0.0531
	(1.97)	(1.92)	(1.84)	(1.58)	(1.19)	(0.75)	(0.31)
Redemption Fee	0.0293*	0.0582	0.0811	0.1194	0.1127	0.2170	0.0774
	(1.66)	(1.50)	(1.34)	(0.96)	(0.43)	(0.56)	(0.15)
Ln(Total AUM)	-0.0030***	-0.0064***	-0.0101***	-0.0219***	-0.0472***	-0.0735***	-0.0997***
	(-4.16)	(-4.26)	(-4.35)	(-4.41)	(-4.42)	(-4.60)	(-4.58)
Ln(Firm Age)	-0.0014	-0.0021	-0.0033	-0.0015	0.0003	-0.0104	-0.0477
	(-0.52)	(-0.37)	(-0.38)	(-0.08)	(0.01)	(-0.17)	(-0.54)
Avg. Flows to Fund Style	0.1095**	0.2073**	0.2584*	0.1958	-0.0591	-0.7342	-1.7104
	(2.10)	(2.07)	(1.74)	(0.67)	(-0.09)	(-0.71)	(-1.14)
Advisor FE	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y
Observations	74234	73122	72027	68807	62573	57232	52062
Number of Advisors	1021	1013	1007	999	872	857	759
Adjusted R^2	0.30	0.38	0.43	0.49	0.55	0.58	0.60

Table 2.8: Post-Misconduct Changes in Fees and Contractual Incentives

This table provides regression result of fees and contractual incentives on mutual fund advisory misconduct. The sample consists of fund-year observations from 2000 to 2013. The dependent variables of fees in year $t+1$ include 12b-1 fee, and among them, fee paid to underwriter and broker-dealer, scaled by total net assets. The dependent variables of contractual incentives in year $t+1$ include Cole's Incentive Ratio (Cole's IR), Weighted Incentive Ratio (Weighted IR) and Dollar Incentive Ratio (Dollar IR). The main explanatory variable *Mutual Fund Misconduct Dummy* equals one if an advisor commits at least one advisory misconduct case in year t. *Ln(Past Monetary Fine)* is log of monetary fine associated with all misconduct of an advisor as of year t. *Lagged Fund Returns* is funds' annual returns in year t. *Lagged Fund Flows* is funds' netflows in year t. Detailed definitions of other control variables are provided in Appendix A.8. All regressions include fund and year fixed effects. The robust t-statistics clustered by fund are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Fee			Contractual Incentive		
	(1)	(2)	(3)	(4)	(5)	(6)
	12b-1 Fee	Underwriter	Broker-Dealer	Coles's IR	Weighted IR	Dollar IR
Mutual Fund Misconduct Dummy	0.0030*	0.0069***	-0.0019**	-0.0044***	-0.0017*	-0.7177**
	(1.88)	(4.07)	(-2.26)	(-2.90)	(-1.87)	(-2.22)
Ln(Past Monetary Fine)	-0.0006***	-0.0006***	0.0001*	0.0002	0.0002	0.0826***
	(-3.53)	(-3.95)	(1.83)	(1.04)	(1.47)	(3.42)
Lagged Fund Returns	0.0010	0.0036***	-0.0039***	-0.0013	-0.0000	0.0340
	(0.59)	(2.99)	(-3.87)	(-1.06)	(-0.02)	(0.13)
Lagged Fund Flows	-0.0630***	-0.0234**	-0.0156**	-0.0070	-0.0037	-5.7490***
	(-4.33)	(-2.42)	(-2.09)	(-0.41)	(-0.40)	(-3.42)
Ln(Fund TNA)	0.0133***	0.0060***	0.0034***	-0.0085***	-0.0038***	-2.4574***
	(9.16)	(5.68)	(4.54)	(-7.60)	(-6.70)	(-11.12)
Ln(Fund Age)	0.0079***	0.0117***	0.0001	-0.0187***	-0.0101***	-1.5286***
	(2.76)	(5.46)	(0.05)	(-6.50)	(-6.12)	(-3.78)
Expense Ratio	-0.0026**	0.0017**	-0.0020***	-0.0017***	-0.0009***	-0.6647***
	(-2.01)	(2.29)	(-2.88)	(-2.75)	(-2.86)	(-6.16)
Front-End Load	0.0329**	0.0108	0.0081	0.0042	0.0025	-4.8776***
	(2.08)	(0.96)	(0.84)	(0.62)	(0.75)	(-4.04)
Redemption Fee	0.4192***	0.2334***	0.1057***	0.0271	0.0025	-2.0279
	(8.30)	(6.42)	(4.61)	(1.38)	(0.21)	(-0.73)
Ln(Fund Family TNA)	0.0006	0.0003	0.0004	-0.0009	-0.0004	-0.2215***
	(0.96)	(0.72)	(1.27)	(-1.25)	(-1.25)	(-3.65)
Flow to Fund Style	0.0121	0.0592	-0.0571	-0.0572	-0.0187	-1.0e+02***
	(0.15)	(0.97)	(-1.23)	(-0.79)	(-0.50)	(-7.04)
Fund FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	50728	50728	50728	52659	52659	52105
Number of Funds	11350	11350	11350	11824	11824	11696
Adjusted R^2	0.87	0.88	0.80	0.85	0.84	0.44

Table 2.9: Post-Misconduct Changes in Investment Restrictions

This table provides result of linear probability model of investment restrictions and actual usage of investment vehicles on mutual fund advisory misconduct. The sample consists of fund-year observations from 2000 to 2013. The dependent variables for investment restrictions are indicators equal to one if a certain type of investment vehicle is prohibited by investment policies in year $t+1$; The dependent variables for actual usage are indicators equal to one if a certain type of investment vehicle is actually used in year $t+1$. The main explanatory variable *Mutual Fund Misconduct Dummy* equals one if an advisor commits at least one mutual fund advisory misconduct case in year t, and zero otherwise. *Ln(Past Monetary Fine)* is log of monetary fine associated with all misconduct of an advisor as of year t. *Lagged Fund Returns* is funds' annual returns in year t. *Lagged Fund Flows* is funds' netflows in year t. Detailed definitions of other control variables are provided in Appendix A.8. All regressions include fund style and year fixed effects. The robust t-statistics clustered by fund are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Investment Restriction			Actual Usage		
	(1)	(2)	(3)	(4)	(5)	(6)
	Options	Futures	Foreign Stock	Options	Futures	Foreign Stock
Mutual Fund Misconduct Dummy	-0.0067***	-0.0045***	-0.0069***	0.0222***	-0.0113	0.0245***
	(-4.19)	(-2.58)	(-4.26)	(3.57)	(-1.33)	(2.84)
Ln(Past Monetary Fine)	-0.0003***	-0.0003***	-0.0004***	-0.0002	0.0026***	0.0040***
	(-4.33)	(-4.51)	(-5.18)	(-0.57)	(5.66)	(7.74)
Lagged Fund Returns	-0.0039*	-0.0049**	-0.0056**	-0.0020	-0.0127*	0.0526***
	(-1.76)	(-2.12)	(-2.41)	(-0.35)	(-1.78)	(6.43)
Lagged Fund Flows	-0.0157	-0.0263*	-0.0179	0.0564*	-0.2098***	-0.1793***
	(-1.06)	(-1.80)	(-1.12)	(1.65)	(-5.02)	(-2.83)
Ln(Fund TNA)	-0.0005	-0.0006**	-0.0011***	0.0181***	0.0095***	0.0518***
	(-1.48)	(-1.96)	(-3.13)	(12.41)	(4.91)	(21.60)
Ln(Fund Age)	-0.0033***	-0.0037***	-0.0039***	-0.0093***	0.0141***	0.0030
	(-4.03)	(-4.66)	(-4.79)	(-2.74)	(2.98)	(0.55)
Expense Ratio	-0.0017**	-0.0004	-0.0021***	0.0390***	0.0130***	0.0712***
	(-2.31)	(-0.48)	(-2.80)	(13.87)	(4.56)	(16.41)
Front-End Load	0.0003	-0.0007	-0.0130**	-0.0265	-0.0425*	-0.1875***
	(0.04)	(-0.11)	(-2.21)	(-1.40)	(-1.95)	(-5.92)
Redemption Fee	0.0178	0.0101	0.0133	-0.0254	-0.0195	0.1380
	(0.79)	(0.46)	(0.61)	(-0.40)	(-0.26)	(1.39)
Ln(Fund Family TNA)	-0.0010***	-0.0004*	-0.0001	-0.0035***	0.0127***	0.0015
	(-4.49)	(-1.89)	(-0.62)	(-4.26)	(11.27)	(0.99)
Flow to Fund Style	0.3603***	0.2909**	0.5072***	0.2693	1.8977***	0.9818**
	(3.12)	(2.56)	(4.81)	(1.01)	(5.63)	(2.57)
Fund Style FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	57718	57718	57718	57718	57718	57718
Number of Funds	16883	16883	16883	16883	16883	16883
Adjusted R^2	0.01	0.01	0.01	0.03	0.08	0.21

Table 2.10: Misconduct and Advisor Replacement

This table provides result of linear probability and Lgoit model of advisor replacement on mutual fund advisory misconduct. The sample consists of fund-year observations from 2000 to 2013. The dependent variable is an indicator equals to one if the current advisor is replaced in year $t + 1$. The main explanatory variable *Mutual Fund Misconduct Dummy* equals one if an advisor commits at least one mutual fund advisory misconduct case in year t, and zero otherwise. *Ln(Past Monetary Fine)* is log of monetary fine associated with all misconduct of an advisor as of year t. *Lagged Fund Returns* is funds' annual returns in year t. *Lagged Fund Flows* is funds' netflows in year t. Detailed definitions of other control variables are provided in Appendix A.8. Both models include year and fund style fixed effects, and report original coefficient estimates. The R^2 for LPM is adjusted R^2, while the R^2 for Logit model is pseudo R^2. The robust t-statistics clustered by fund are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	LPM		Logit	
	(1)	(2)	(3)	(4)
Mutual Fund Misconduct Dummy	0.0125***	0.0130***	0.4112***	0.4310***
	(3.50)	(3.62)	(3.92)	(4.10)
Ln(Past Monetary Fine)	0.0001	0.0002*	0.0030	0.0073*
	(0.76)	(1.81)	(0.79)	(1.83)
Lagged Fund Returns	-0.0012	0.0001	-0.0539	-0.0079
	(-0.43)	(0.03)	(-0.53)	(-0.08)
Lagged Fund Flows	-0.0065	0.0130	-0.2471	0.4899
	(-0.34)	(0.65)	(-0.34)	(0.68)
Ln(Fund TNA)		0.0018***		0.0674***
		(3.92)		(3.89)
Ln(Fund Age)		0.0049***		0.1943***
		(4.30)		(4.40)
Expense Ratio		0.0022**		0.0814***
		(2.44)		(2.72)
Front-End Load		-0.0013		-0.0560
		(-0.18)		(-0.23)
Redemption Fee		0.0737***		2.0829***
		(2.63)		(3.03)
Ln(Fund Family TNA)		-0.0013***		-0.0488***
		(-4.19)		(-4.35)
Flow to Fund Style		0.1373		3.6292
		(0.94)		(0.83)
Fund Style FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	57815	57726	57815	57726
Number of Funds	16907	16884	16907	16884
R^2	0.01	0.01	0.02	0.03

Table 2.11: Misconduct and Advisor Survival

This table provides result of linear probability and Logit model of advisors' business failure on mutual fund advisory misconduct. The sample consists of advisor-year observations from 2000 to 2013. The dependent variables are *Closure*, an indicator equals one if an advisor closes advisory business in year $t + 1$; and *Takeover*, an indicator equals one if the advisor is acquired or succeed in year $t + 1$. The main explanatory variable *Mutual Fund Misconduct Dummy* equals one if an advisor commits at least one mutual fund advisory misconduct case in year t, and zero otherwise. *Ln(Past Monetary Fine)* is log of monetary fine associated with all kinds of misconduct of an advisor as of year t. *Lagged Returns* is TNA-weighted average returns of all funds managed by an advisor in year t. *Lagged Flows* is aggregate netflows of an advisor in year t. Detailed definitions of other control variables are provided in Appendix A.8. Both models include year fixed effects, and report original coefficient estimates. The R^2 for LPM is adjusted R^2, while the R^2 for Logit model is pseudo R^2. The robust t-statistics clustered by advisor are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	LPM		Logit	
	(1)	(2)	(3)	(4)
	Closure	Takeover	Closure	Takeover
Mutual Fund Misconduct Dummy	0.0033	0.0302*	0.2532	1.4179***
	(0.32)	(1.83)	(0.32)	(2.77)
Ln(Past Monetary Fine)	0.0007**	-0.0000	0.0461*	-0.0004
	(2.40)	(-0.07)	(1.93)	(-0.02)
Lagged Returns	0.0060	-0.0119**	0.4092	-1.1552**
	(0.67)	(-2.37)	(0.92)	(-2.57)
Lagged Flows	-0.0076	-0.0243	-0.7039	-2.9452
	(-0.27)	(-1.30)	(-0.36)	(-1.03)
Front-End Load	-0.0158	0.0002	-0.8107	0.0448
	(-1.07)	(0.01)	(-0.89)	(0.03)
Expense Ratio	0.0048*	-0.0012	0.0879	-0.1476
	(1.84)	(-1.12)	(1.49)	(-0.99)
Redemption Fee	-0.0863	0.0650	-3.6922	4.1261*
	(-1.62)	(1.34)	(-0.89)	(1.79)
Ln(Total AUM)	-0.0041***	0.0001	-0.2706***	0.0052
	(-4.45)	(0.15)	(-7.01)	(0.12)
Ln(Firm Age)	-0.0309***	-0.0043	-1.0399***	-0.3866
	(-3.09)	(-0.67)	(-3.70)	(-0.69)
Avg. Flows to Fund Style	-0.0169	-0.0220	-1.3326	-2.0894
	(-0.80)	(-1.13)	(-0.84)	(-1.08)
Year FE	Y	Y	Y	Y
Observations	6534	7023	6534	7023
Number of Advisors	1100	1142	1100	1142
R^2	0.02	0.00	0.12	0.04

Table 2.12: Misconduct and Advisor Performance

This table provides regression result of advisors' future aggregate returns on mutual fund advisory misconduct. The sample consists of advisor-year observations from 2000 to 2013. The dependent variable is cumulative aggregate advisors' returns from year t up to year $t+n$ (n=1,2), where aggregate advisors' returns are calculated as the TNA-weighed average of returns of mutual funds managed by a particular advisor. The main explanatory variable *Mutual Fund Misconduct Dummy* equals one if an advisor commits at least one mutual fund advisory misconduct case in year t, and zero otherwise. *Ln(Past Monetary Fine)* is log of monetary fine associated with all misconduct of an advisor as of year t. *Lagged Returns* is TNA-average return of the funds managed by the advisor in year t. *Lagged Flows* is aggregate net-flows of an advisor in year t. Detailed definitions of other control variables are provided in Appendix A.8. The robust t-statistics clustered by advisor are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Full Sample		Upturn	Downturn
	(1)	(2)	(3)	(4)
	t+1	(t+1,t+2)	(t+1,t+2)	(t+1,t+2)
Mutual Fund Misconduct Dummy	-0.0383**	-0.0771***	-0.0960**	-0.0401
	(-2.20)	(-2.59)	(-2.33)	(-1.09)
Ln(Past Monetary Fine)	0.0013**	0.0029***	0.0014	0.0024
	(2.56)	(2.71)	(1.28)	(1.55)
Lagged Returns	-0.0195	-0.2130***	-0.1002**	-0.6785***
	(-1.09)	(-7.69)	(-2.33)	(-14.72)
Lagged Flows	-0.0290	-0.0070	0.0651	0.1651
	(-0.60)	(-0.10)	(0.71)	(1.55)
Expense Ratio	0.0060	0.0064	0.0025	-0.0058
	(1.31)	(0.68)	(0.24)	(-0.54)
Front-End Load	-0.0469	-0.0701	0.0448	-0.0858
	(-1.17)	(-0.98)	(0.71)	(-0.77)
Redemption Fee	0.1995	0.3308	0.4413	0.4158
	(0.94)	(0.84)	(1.02)	(0.90)
Ln(Total AUM)	0.0005	-0.0033	-0.0036	-0.0040
	(0.41)	(-1.41)	(-1.28)	(-1.15)
Ln(Firm Age)	0.0105***	0.0143**	0.0066	0.0034
	(3.03)	(2.39)	(1.00)	(0.35)
Observations	5295	4223	2543	1680
Number of Advisors	890	754	650	619
Adjusted R^2	0.00	0.03	0.01	0.19

CHAPTER 3

ARE INTERFUND LENDING PROGRAMS EFFECTIVE?

3.1 Introduction

The cross-subsidization and internal capital market in the fund family has attracted increasing academic attentions over the past decades. Gaspar et al. (2006), for example, shows the evidence of strategic cross-subsidization for “high family value” funds (i.e., high fees or high past performers) at the cost of “low value” funds, and the performance gap is partly driven by favourable trades for those high value funds. The cross-trades between funds affiliated to the same institution are used either to opportunistically reallocate performance among trading funds or to reduce transaction costs for both counterparties, and generate greater mis-pricing in favor of “star” funds Eisele et al. (2017). Goncalves-Pinto and Schmidt (2013) shows that the off-exchange cross-trades are mainly the outcome of coordinated strategies at the fund manager level. In addition to the general discussion of the cross-subsidization among mutual funds, there have been emerging studies investigating the function of internal capital market within the fund family. Bhattacharya et al. (2013), among others, discovers the role of insurance pool against temporary liquidity shocks to other funds in the family for affiliated funds of mutual funds (AFoMFs). Goncalves-Pinto and Sotes-Paladino (2016) also finds that internal markets of fund families play a key role in inducing member funds to engage in risk-shifting trades with other funds in the family, leading to deviation excessively from their investment mandates.

While most of the existing literature highlights the role of internal capital market in cross-subsidization and point to the potential negative consequences for fund investors due to conflict of interest, another channel of liquidity provision under severe distress events has received relatively little attention until recently. Agarwal and Zhao (2017), for the first time, documents the incentive of fund families to apply for regulatory exemptions to participate in Interfund Lending Programs, the economic consequences of the Interfund Lending Programs on portfolio holdings, and its mitigating role in stock fire sales following investor outflows.[1] The Interfund Lending Programs serve as a alternative way of short-term liquidity provision between borrowing and lending funds in the fund family. It is designed in such a mechanism that the borrowing (lending) rate associated with Interfund Lending Programs should be lower (higher) than market rate, thus creating mutual benefits for the two counterparties involved in the deals. However, there is a lack of empirical evidence concerning the the effectiveness of Interfund Lending Programs in the mutual fund industry. In this paper, we evaluate the effectiveness of Interfund Lending Programs by examining how they benefit both borrowing and lending funds during distress time.

To test my hypothesis, we construct a weekly panel dataset using N-SAR filings and CRSP Mutual Fund Database. Weekly fund returns are calculate from daily fund-share class returns from CRSP, and aggregated at fund level. We then merge CRSP Mutual Fund Database with N-SAR fillings to obtain fund characteristics, including family affiliation for each funds. The strength of N-SAR filings is that it contains the precise information of fund family affiliation, with a unique family identifier. The exact date of ILP application and approval

[1]The consequences of asset fire sales on equity prices have been studied extensively. Two recent works on the asset fire sales in mutual fund industry include Khan, Kogan, and Serafeim (2012) and Jotikasthira et al. (2012).

for each fund family after 2008 is collected from the SEC public disclosure. We manually search Federal Register using key words 'interfund lending' and 'exemptive order' to get the same information prior to 2008.

We begin our analysis with baseline regression where the fund's weekly returns are regressed on a ILP indicator along with the interaction term Distress×ILP. The distress events are defined in the sense that the funds belonging to a specific investment style suffer from large negative shock in weekly returns. The definition suggests that the distress events are most likely exogenous to fund characteristics, and thus not subject to endogeneity concern that tremendous under-performance is driven by poor investment skills of managers. The distress events are defined at alternative magnitudes, namely, TNA-weighted weekly returns of funds with the same investment style are below the bottom 3rd, 2nd, 1th, 0.5th and 0.25th percentile of the same funds' weekly returns during the whole sample period. These distress events capture negative return shocks in increasing magnitude order. We find that the funds with Interfund Lending Programs have 0.33% higher returns than non-ILP funds in the week following the distress with most strict definition. This suggests a positive role of Interfund Lending Programs in providing short-term liquidity to funds in distress, thus avoiding asset fire sales at the cost of fund investors. In the meanwhile, we do not find empirical evidence concerning the benefit of Interfund Lending Programs for lending funds. Lending funds with Interfund Lending Programs do not have significantly higher returns than non-ILP funds following distress events. This indicates that lending funds might not benefit from Interfund Lending Programs through short-term lending to borrowing funds in distress.

The benefit of Interfund Lending Programs for borrowing and lending funds might be related to other factors are haven't been considered in our baseline regressions. For instance, fund liquidity plays a key role in the effectiveness of Interfund Lending Programs for both parties. This is because illiquid funds facing distress have more difficulties in meeting redemption needs. Thus they tend to borrow money through Interfund Lending Programs to circumvent potential costly asset fire sales. Similarly, the effectiveness of Interfund Lending Programs for borrowing funds are more pronounced during period of high external funding cost, which is recognized as indicator of low credit availability in the market. Lastly, the diversity of intra-family investment styles are also important in affecting the effectiveness of Interfund Lending Programs, since more diversified fund family have greater flexibility in the timing of liquidity supply, especially when the distress events are considered exogenous to the fundamentals of mutual funds. We re-examine our hypothesis with sub-samples that are conditional on these attributes and find results that are consistent with our predictions. Overall, the effectiveness of Interfund Lending Programs for borrowing funds are predominant for more illiquid funds, during period of high external funding cost, and for funds affiliated with families having diversified investment styles. However, we find limited evidence concerning the role of these factors in the effectiveness of Interfund Lending Programs for lending funds. For example, the benefit of Interfund Lending Programs for lending funds are larger for liquid funds, but credit market liquidity and family diversity does not play a role in affecting the effectiveness of Interfund Lending Programs.

Our baseline regression might fail to consider the heterogeneity among funds that with and without Interfund Lending Programs. Note that the decision of applying for Interfund Lending Programs can be endogenous, since it is dependent on the fund characteristics in the family. To address the potential concern for the fund heterogeneity issue in the baseline regressions, we conduct our analysis based on a matched sample around a particular period of time, known as extreme market downside, around the September 2008 following the collapse of Lehman Brothers. The reason for focusing on this specific period is that most of the distress events are concentrated in the third week in September 2008, and they are recognized as financial market turmoil not related to fund-specific characteristics. We define treatment funds as funds in the families that have Interfund Lending Programs, and define control funds as those do not have Interfund Lending Programs. We further match treatment and control funds based on fund size, age, expense ratio, front-end load and redemption fees. We also require that treatment and control funds should have the same CRSP 4-digit style code. Our results of the matched sample confirms our primary findings, and show that the borrowing funds have 0.30% higher returns than non-ILP funds during the crisis episode and the most strict definition of distress events is used. It suggests that our findings remain quantitatively similar when heterogeneity among treatment and control funds has been addressed.

We also conduct a series of robustness checks to ensure that our findings are robust to alternative variable definition, sample period and additional controls. First, we use two alternative definitions of distress events. Instead of using original CRSP 4-digit style code, we define our distress events using the first two digit of CRSP style code. The first two digit of the style code reflect board investment styles which capture negative shock in returns for a much larger number of funds within the style. Alternatively, instead of using bottom percentile of style returns, we apply fixed return thresholds, from -2% up to -6% of weekly returns, to define distress events. This method imposes fixed cutoff points for all styles, and will lead to different number of distress events for each investment style, given the riskiness of their portfolios and returns volatilities. In general, our results demonstrate that the borrowing funds through Interfund Lending Programs have greater capability of dealing with outflows and redemption pressure from fund investors. They have 0.13%-0.35% higher returns in the week following extreme distress. While the benefit of Interfund Lending Programs for borrowing funds are economically sizeable, it has little effect for lending funds, partly because there is cross-subsidization among fund family, and lending funds does not have enough benefit that outweigh the costs. In addition, we also check the robustness of our findings by excluding 2008-2009 financial crisis, using exact date of SEC exemptive order for Interfund Lending Programs, and including additional fund-level controls. All our results remain quantitatively the same.

Our paper contributes to three strands of literature. First, it is closely related to prior studies on the cross-subsidization among mutual funds in the same family. Gaspar et al. (2006), Bhattacharya et al. (2013), and Goncalves-Pinto and Schmidt (2013), among others, demonstrate the existence of cross-subsidization within fund family in favor of partial set of funds at the cost of fund investors. The cross-subsidization usually takes form of cross-trading the securities, or off-exchange transactions associated with high degree of mispricings Eisele et al. (2016); Goncalves-Pinto and Sotes-Paladino (2016). Our paper shows one additional channel of cross-subsidization that is mutually beneficial for two parities involved in the deal: the interfund lending facilities which provides necessary liquidity to funds under extreme distress.

Our paper also contribute to the studies on the liquidity management in mutual funds. For example, Chernenko and Sunderam (2016) finds that mutual funds hold substantial amounts of cash to accommodate inflows and outflows, especially for funds with illiquid assets and at times of low market liquidity. Similarly, Ben-Rephael (2017) and Rzeznik (2017) demonstrates an increase in the liquidity of funds' portfolio under extreme market uncertainty, known as flight-to-liquidity. These studies are extension of findings in Coval and Stafford (2007) and Dong, Krystyniak, and Peng (2016), which documents possible trading strategy following liquidity shocks.[2]

Finally, our paper is complement to Eisele et al. (2013) and Evans et al. (2017b), which document behavioral difference among competitive and cooperative fund managers within fund families. While Eisele et al. (2013) suggests that fund managers front-run their distressed peers under coordination of the family, our results seem to be in line with the hypothesis in support of the positive role of lending funds. Our result that cooperative managers are more likely engaged in interfund lending facilities is consistent with Evans et al. (2017b), which suggests more intensive cross-subsidization for families with more cooperative incentives.

[2]Honkanen and Schmidt (2017) find that such profitability spills over onto the stock returns of economic peers.

3.2 Data and Methodology

3.2.1 Data

We collect the data from three major sources. First, fund returns and investment style code are obtained from CRSP Survivor-Bias-Free US Mutual Fund Database. Weekly fund returns are calcualted as TNA-weighed average of daily returns if funds have multiple share classes. The second data source is Form N-SAR. The Form N-SAR is semi-annual report for registered investment companies, which includes identification, gross flows, advisory contract terms, and accounting information. We match CRSP Mutual Fund Database with N-SAR filings by names of funds and investment companies. The matching takes two rounds. In the first round, we match by exact name of funds and investment companies. In the second round, we apply fuzzy match on names while requiring less than 5% deviation in total net assets. The two-round procedure matches over 75% of the CRSP fund-share identifiers.[3] The unique strength of N-SAR filing is that it provides fund family affiliation for each fund, while CRSP Mutual Fund Database lacks such critical information.

Finally, we manually collect application and approval date of SEC exemptive order for Interfund Lending Programs from Investment Company Act Notices and Orders Category Listing on the SEC website.[4] Each notice filing contains full context of SEC exemptive order, which specify the fund family and its affiliated mutual funds that applied for the Interfund Lending Program. We match

[3]The name of funds in CRSP Mutual Fund Database has three components: fund name, trust name and share-class name, with question mark in between. We use this pattern to split the name into three components and match them with N-SAR.

[4]https://www.sec.gov/rules/icreleases.shtml#interfundlending.

these fund families with family identifier in N-SAR filings (N-SAR Item 19). However, the SEC public disclosure of application and exemptive order date only covers period following 2008. Therefore, we complement with exact application date for Interfund Lending Programs by manually searching Federal Register using keywords such as "interfund lending" and "exemptive order".[5] To fill in missing approval data prior to 2008, we use the average time interval between application and order after 2008, which is approximately 350 days. Table A.10 show the date of application and exemptive order for each Interfund Lending Program.

3.2.2 Methodology

Our empirical methodology applies two sets of panel regressions to examine the effectiveness of Interfund Lending Programs for borrowing and lending funds within the fund family. Specifically, on the borrowing side, we test whether funds that are eligible for Interfund Lending Programs suffer less from extremely negative return shocks than those ineligible for Interfund Lending Programs. On the lending side, we examine whether funds with Interfund Lending Programs have higher returns than non-ILP funds when there are distress funds in the families. Our definition of style-wide distress involves several thresholds. We define distress in the sense that the TNA-weighted weekly returns of funds with investment objective k are below the bottom 3rd, 2nd, 1th, 0.5th and 0.25th percentile of the same funds' weekly returns during the whole sample period, respectively. The smaller the threshold, the fewer distress events and stronger liquidity needs for funds. We regard the extreme negative returns shock as dis-

[5] https://www.federalregister.gov/

tress because it leads to large flow outflows, creating redemption pressure and liquidity shortage. To avoid endogenous problem, we define distress at investment style level rather than individual fund level. This is out of concern fund's distress might be correlated with managerial investment skills, and thus driven by individual fund characteristics.

Effectiveness of Interfund Lending Programs for Borrowing Funds

On the borrowing side, we evaluate the effectiveness of Interfund Lending Programs for borrowing funds with following regression:

$$r_{i,j,k,t+1} = \beta \text{Distress}_{k,t} \times \text{ILP}_{j,t} + \gamma \text{ILP}_{j,t} + \theta_i + \delta_{k,t} + \epsilon_{i,t} \tag{3.1}$$

where $r_{i,j,k,t+1}$ is the return of fund i, belonging to fund family j with investment style k in week $t+1$. We include fund fixed effect θ_i to account for managerial skills, or any time-invariant fund characteristics. We also control for style-time fixed effect $\delta_{k,t}$ to address the heterogeneity of investment styles. The style-wide distress indicator $\text{Distress}_{k,t}$ is a dummy variable equals one if average weekly return of funds with investment style k is below the bottom 3rd, 2nd, 1th, 0.5th and 0.25th percentile of the same funds' weekly returns during the whole sample period, respectively. $\text{ILP}_{j,t}$ is a dummy variable equals one the time period after SEC exemptive order of Interfund Lending Program for fund family j. The standard errors are clustered by fund family and time.

When funds are in exogenous distress, they face great liquidity needs. The Interfund Lending Programs can act as short-term liquidity provider for borrowing funds, contributing to less price pressure from asset fire sales. Therefore, we hypothesize that ILP-funds suffer less than non ILP-funds following distress events. In other words, the coefficient of interest β should be significantly positive.

Effectiveness of Interfund Lending Programs for Lending Funds

Similarly, on the lending side, we examine the effectiveness of Interfund Lending Programs for lending funds with the following regression:

$$r_{i,j,k,t+1} = \beta \text{Distress}_{\not{k},j,t} \times \text{ILP}_{j,t} + \gamma \text{ILP}_{j,t} + \theta_i + \delta_{k,t} + \epsilon_{i,t} \tag{3.2}$$

where $r_{i,j,k,t+1}$ is the return of fund i, belonging to fund family j with investment style k in week $t + 1$. We also control for fund and style-time fixed effects, as Equation 3.1. $\text{ILP}_{j,t}$ is a dummy variable equals one the time period after SEC exemptive order of Interfund Lending Program for fund family j. A slight variation is for the definition of $\text{Distress}_{\not{k},j,t-1}$, which is a dummy variable equals one if funds with investment style other than k experiences distress. The standard errors are clustered by fund family and time.

Since The lending funds can benefit from Interfund Lending Programs by earning interest income higher than market rate, we postulate that funds with Interfund Lending Programs have higher returns than non ILP-funds when there are distressed funds in the families. Therefore, we would find positive and significant coefficient β.

3.2.3 Summary Statistics

Figure 3.1 presents number of distressed funds over time for different thresholds in distress definition. Most of the distressed events are clustered around

September 2008 during financial crisis. Panel D of 3.1 shows that this pattern becomes even more pronounced when mutual funds experience extremely low style-wide negative return shocks, which are below the bottom 0.25 percentile of the same funds' weekly returns over the entire sample period. In addition to 2008 financial crisis. other major distress events take place at Internet bubbles around 2000-2001.

Table 3.1 reports the summary statistics of style-wide distress events. The distress events are defined in the sense that the TNA-weighted weekly returns of funds with investment style k are below the bottom 0.5 percentile of the same funds' weekly returns during the whole sample period. The result shows that the probability of distressed funds are very close to the pre-specified 0.5th percentile return threshold. The average weekly returns for distressed funds is below -15% for equity funds, and mostly are below -3% for bond funds. The return distribution suggests that distressed funds face extremely low performance, leading to potential outflows.

Summary statistics of main variables are presented in Table 3.2. The sample consists of fund-week observations from 1998 to 2014. First, about 30% of fund-week observations are from funds that are eligible for Interfund Lending Programs. The mean (median) weekly fund returns are 0.12% (0.08%), with standard deviation of 2.21%. In addition, average fund TNA is 1.85 billion U.S. dollars, and average fund age is 5.35 years. In terms of investment style, 42% of the fund-week observations are from funds that invest in domestic equities, followed by 13% investing in foreign equities and 11% in municipal bonds.

3.3 Empirical Results

3.3.1 Baseline Regression

We start with estimating the baseline regressions as specification 3.1 and 3.2 for borrowing and lending funds separately. Table 3.3 reports the baseline regression results. Column (1)-(5) show the effectiveness of Interfund Lending Programs for borrowing funds. Our main variable of interest, interaction term Distress×ILP increases in both economic magnitude and t-statistics along with the severity of distress. To be specific, the coefficient increases from 0.0005 in Column (1) to 0.0032 in Column (5), and the t-statistics also increase from 1.63 to 5.63. For example, for distress defined at bottom 0.25th percentile, the funds that are eligible for Interfund Lending Programs have 0.32% higher returns than non-ILP funds in the week immediately following distress events, and the positive effect is highly significant at 1% level. This is consistent with the notion that Interfund Lending Programs will be more effective in providing necessary short-term liquidity to distressed funds when those funds have high liquidity needs under severe distress. The Interfund Lending Programs is helpful for reducing adverse price impact for borrowing funds resulted from asset fire sales following distress.

The effectiveness of Interfund Lending Programs for lending funds is reported in Column (6)-(10) of Table 3.3. We find that Interfund Lending Programs do not have positive effect for lending funds in the families. The primary variable of interest Distress×ILP, the interaction term between ILP indicator and distress dummy is significantly negative for distress events defined at bottom 3rd, 2nd and 1st return threshold, and become insignificant for extreme distress events defined at 0.5th or 0.25th percentile level. It suggests that although lending funds provide short-term liquidity to distressed funds and earn interest income, they do not have significantly higher returns than non-ILP funds which are not eligible for lending. The evidence suggests that the benefits of Interfund Lending Programs for lending funds doesn't outweigh the potential costs. It also indicates that there might be cross-subsidization within fund families.

To examine the effectiveness of Interfund Lending Programs for both borrowing and lending funds in the relatively short term following distress events, we regress the cumulative fund returns over the next 8 weeks from $t + 1$ up to $t + 8$, on the interaction term Distress×ILP and ILP indicator ILP, controlling for fund and style-time fixed effects. The coefficient and its 95% confidence interval is shown in Figure 3.3. Panel A of Figure 3.3 shows that the positive effect of Interfund Lending Programs for borrowing funds is persistent over the next two months following distress events, with significant 0.3% higher cumulative fund returns at the end of the eighth week. This suggests that the positive effect of Interfund Lending Programs for borrowing funds is more than contemporaneous. In contrast, we find no evidence of effectiveness of Interfund Lending Programs for lending funds, as the coefficient of Distress×ILP in Panel B is not significantly different from zero.

3.3.2 Sub-Sample Analysis

Broad Investment Style

To evaluate the effectiveness of Interfund Lending Programs for each asset class, we run the baseline regression by board investment styles. The broad investment style is classified using the first 2 digits of CRSP investment style code. These broad investment styles reflect the riskiness and liquidity of their portfolio holdings. They include domestic equities (ED), foreign equities (EF), corporate fixed income (IC), foreign fixed income (IF), government fixed income (IG), money market fixed income (IM), municipal fixed income (IU) and balanced funds (M). We also control for style-time and fund fixed effects, and cluster standard error by fund.[6]

Panel A of Table 3.4 presents the effect of Interfund Lending Programs on fund returns following exogenous negative return shocks for each board investment style. We find that the positive effect of Interfund Lending Programs for borrowing funds are mostly concentrated in equity (ED and EF) and municipal funds (IU), as indicated by the positive and significant interaction term Distress×ILP. For instance, on average domestic equity funds have 0.53% higher returns in the week following extreme distress defined at bottom 0.25th percentile level, followed by foreign equity funds (0.39%) and municipal funds (0.18%). All these coefficients are highly significant at 1% level. Figure 3.4 reports the coefficient of interaction term $\text{Distress}_{k,t} \times \text{ILP}_{j,t}$ (solid) and its 95% confidence interval (dash) for each broad investment style over the next two months following distress events. The positive effect of Interfund Lending Programs on fund returns persists for the following two months for domestic equity funds, while the effect for municipal funds lasts for about two weeks.

Panel B of Table 3.4 shows the result for lending funds. In general, we find that funds investing in foreign equities and government bond benefit from the Interfund Lending Programs, as their returns are higher than non-ILP funds in

[6]We find that clustering standard errors by fund family will lead to extremely large t-statistics due to non-semidefinite variance-covariance matrix.

the following week after distress events. The effect is statistically significant and economically sizeable, as these two groups of funds have 0.16%-0.18% higher returns than non-ILP funds, with large t-statistics over 4. For domestic equity funds and money market funds, though statistically significant, the economic magnitude is relative small and negligible. The result for lending funds is consistent with the hypothesis that Interfund Lending Programs are more effective for lending funds that hold liquid assets, since they have the flexibility in providing short-term liquidity to distressed funds in the families. Figure 3.5 reports the coefficient of $\text{Distress}_{k,j,t} \times \text{ILP}_{j,t}$ (solid) and its 95% confidence interval (dash) for each broad investment style over the following eight weeks following distress events. We confirm the finding that the positive effect of Interfund Lending Programs on fund returns remain statistically significant over two months for money market funds, while it lasts for four to five weeks for government and foreign equity funds.

Credit Market Liquidity

The Interfund Lending Program is designed as lending facility in fund families. They are substitute to external funding sources such as banks and other financial institutions. According to the mechanism of the program, borrowing funds benefit from the lending facilities that provide valuable short-term liquidity at lower cost, while lending funds also charge interest rate higher than federal fund rate. As a consequence, the effectiveness of Interfund Lending Programs for both parties is associated with overall credit market liquidity, measured by TED spread. On one hand, the effectiveness of Interfund Lending Programs for borrowing funds is more pronounced during illiquid credit market, as time period with high TED spread is usually considered as credit constraint in the financial market. On the other hand, external funding cost is not as important for lending funds, since what really matters is the spread between designated interfund lending rate and federal fund rate.

Table 3.5 reports the result of sub-sample analysis conditional on credit market liquidity. Illiquid period is defined as time period when TED rate is above the sample median. Panel A of Table 3.5 shows that consistent with our expectation, the effectiveness of Interfund Lending Programs for borrowing funds are more pronounced during illiquid period. It suggests that when overall credit market is illiquid, the Interfund Lending Programs play a significant role in helping distressed funds meet redemption needs, since it is difficult to obtain external funding from banks or financial institutions. The positive effect of Interfund Lending Programs becomes secondary during low-TED spread period, indicating that distressed funds have easier access to external sources of funding.

Panel B of Table 3.5 shows the result sub-sample analysis for lending funds. Our result shows that the effectiveness of Interfund Lending Programs for lending funds are not driven by credit market liquidity. We find that the Interfund Lending Programs do not have positive effect in both liquid and illiquid periods, as indicated by insignificant or negative interaction term Distress×ILP under alternative distress definitions. Therefore, the general credit market liquidity condition has no effect on the effectiveness of Interfund Lending Programs for lending funds.

Intra-Family Style Diversity

The Interfund Lending Programs serve as internal capital market in fund families. Its role in liquidity provision depends on the existence of liquidity providers. Goncalves-Pinto and Sotes-Paladino (2016) shows that investment style diversity within fund family plays a positive role in offsetting trades across funds. A fund family having funds with various investment styles create more potential sources of liquidity providers. As a result, higher intra-family style diversity in fund families leads to more effective functioning of Interfund Lending Programs. In this section we examine our baseline findings conditional on style diversity within fund family. We hypothesize that the benefit of Interfund Lending Programs for both borrowing funds will be larger if the fund families have more diversified investment styles. But the style diversity does not matter for lending funds. Specifically, high-diversity fund families are defined as having above-median Herfindahl-Hirschman Index (HHI) of fund total net assets, where the HHI is calculated as summation of squared proportion of TNA belonging to the CRSP 4-digit style codes within families. Lower HHI of the fund family indicates more diversified investment styles.

Table 3.6 reports the result of sub-sample analysis conditional on intra-family style diversity. Panel A of Table 3.6 reports the result for borrowing funds. We find that the positive effect of Interfund Lending Programs for borrowing funds is mostly driven by fund families with diversified investment styles. For example, the interaction term Distress×ILP are positive and highly significant under extreme distress defined at bottom 0.25th percentile. Specifically, in the week immediately following distress event, funds with Interfund Lending Programs in high style diversity families have 0.4% higher returns than non-ILP funds. It demonstrates that Interfund Lending Program is more effective for fund families with high style diversity under exogenous negative return shocks. One possible explanation is that high-style diversity families usually have larger number of fund investment styles. The diversity in portfolio holdings and distress timing in fund families contributes to more efficient functioning of internal capital market, creating greater capacity to provide necessary short-term liquidity among funds over time.

Panel B of Table 3.6 reports the result for lending funds. In contrast to the result for borrowers, we find that the effectiveness of Interfund Lending Programs for lending funds is not related to intra-family style diversity. The interaction term Distress×ILP is significantly negative or insignificant in both sub-samples. Therefore, we find no evidence on the role of intra-family style diversity associated with the effectiveness of Interfund Lending Programs for lending funds.

3.3.3 Competitive VS. Cooperative Fund Managers

The mutual fund family applies for Interfund Lending Programs that cover all of the funds within family. The effectiveness of Interfund Lending Programs is somehow dependent on the intra-family manager cooperation. Evans et al. (2017b) and Eisele et al. (2013) discuss two types of managers, namely, competitive and cooperative fund managers. They find evidence consistent with a separating equilibrium, where some fund families encourage cooperation among their managers, while other fund families encourage competition. Funds in families with more cooperative incentives are more likely to engage in cross-subsidization through cross-holding and cross-trading, while funds in families with more competitive incentives are less likely to do so. In the current context, we examine whether the effectiveness of Interfund Lending Programs are associated with the degree of intra-family manager cooperation.

To measure level of manager competition in a fund family, we merge N-SAR with CRSP Mutual Fund Database to obtain fund managers for each fund. Following Evans et al. (2017b), we construct a simplified version of competitive index, which consists of six components. The first five indicator variables are directly obtained from N-SAR fund advisory contract items. First, We include an indicator variable of whether or not the funds advisory fee grows in a linear way with size (Item 48). We hypothesize that managers of funds with a linear percentage advisory fee that remains constant as the fund size grows, have more competitive incentives relative to managers of funds with a concave fee structure, where the fee decreases as fund assets grow. Massa and Patgiri (2009) compares the performance and risk-taking behavior of fund managers with linear vs. concave fund management fee schedules and find evidence of higher performance and risk, consistent with stronger incentives to compete for funds with linear contracts. In addition, We hypothesize that managers of funds rewarded based on that fund's income (Item 49), income or assets (Item 50), or performance (Item 51), are incentivized to be more competitive. The final variable is an indicator which equals one if the fund is managed by a single manager. In the decision to allocate managers across funds, assigning teams of managers to jointly manage multiple funds would naturally encourage cooperation relative to assigning each manager to their own fund. We sum up these six variables for each fund, and take average across all funds in the family in each year. We then divide the sample into two parts using the median value of competitive index.

Table 3.7 presents results of effect of Interfund Lending Programs for the returns of borrowing funds with competitive VS. cooperative fund managers. We find that the effectiveness of Interfund Lending Programs for borrowing funds can be found only for fund families with cooperative managers. The interaction term is positive and significant in most of the specifications. For instance, for distress events defined at bottom 0.25th percentile, funds with Interfund Lending Programs have 0.27% higher returns than non-ILP funds in the week following distress event. It suggests that fund families with more cooperative managers are more willing to provide short-term liquidity through Interfund Lending Programs to the borrowing funds which are facing distress. The aligned interests among fund managers lead to increase availability and timeliness of liquidity provision.

3.3.4 Matched Sample

Although our baseline regression use full-sample data from 1998-2014, it may fail to account for the heterogeneity among funds that are and aren't eligible for Interfund Lending Programs. Therefore our primary findings might be biased might by driven by the difference in fund characteristics that are associated with the application for Interfund Lending Programs. To address this concern, we focus exclusively on a particular sample period when most of the distress events take place. September 2008 is well known for tremendous financial market turmoil. We denote the third week of September 2008 as an exogenous negative return shock that leads to wide-spread distress for mutual funds. The treatment group is eligible for Interfund Lending Program, while control group is ineligible. The event window uses 10 weeks of pre- and post-event period. We use one-to-one nearest neighborhood matching technique to match treatment and control funds based on fund size, fund age, expense ratio, front-end load, redemption fee, past two weeks' return and investment style.[7]

Panel A of Table 3.8 reports the result for unmatched sample. Consistent with our primary findings, we find that the effect of Interfund Lending Programs are positive and highly significant for for distressed funds. Specifically, for the most strict form of distress defined at bottom 0.25th percentile level, the funds with Interfund Lending Programs are associated with 0.35% higher returns than non-ILP funds in the week following distress event, with t-statistics over 3. We find no effect of Interfund Lending Programs for lending funds. Panel B of Table 3.8 reports the result for matched sample. Although the sample size is reduced in half, the variable of interest Distress×ILP remains statistically significant at 5% level, although the economic magnitude is relatively smaller. To be specific, Column (5) shows that for distress events defined at bottom 0.25th percentile level, funds with Interfund Lending Programs on average have 0.19% higher returns than non-ILP funds in one week after distress. Panel C demonstrates the balance test of covariate used for matching. All the covariates except firm age are not significantly different from each other for treatment and control funds after matching, suggesting that the matching has addressed firm heterogeneity problem among funds with and without Interfund Lending Programs.

To examine the effect of Interfund Lending Program for matched sample over time, we regress the cumulative fund returns from week $t+1$ up to $t+8$ on ILP indicator and interaction term Distress×ILP. The the coefficient of Distress×ILP and its 95% confidence interval is presented in Figure 3.6. Panel A of Figure 3.6 shows that the effect of Interfund Lending Programs for borrowing

[7]The matching has caliper of 0.2 and satisfies common support requirement.

funds remains positive and highly significant over the next two months following distress events. The cumulative fund returns amount to 0.5% at the end of the next two months. It indicates that the positive effect of Interfund Lending Programs for borrowing funds is more than contemporaneous, but rather persistent in short term. On the contrary, we find no significant effect of Interfund Lending Programs for lending funds, as the interaction term Distress×ILP in Panel B of Figure 3.6 is not significantly different from zero. In sum, our results from matched sample support the effectiveness of Interfund Lending Programs for borrowing funds after controlling for firm heterogeneity.

3.3.5 Robustness Checks

In this section we conduct a series of robustness checks to our main findings to ensure that our results are not driven by specific variable definition, sample period, or model specifications.

Distress Definitions

In the empirical analysis we defines style-wide distress events based on CRSP 4-digit style code. The CRSP style code consists of over 50 categories. With such detailed classification there are small sample of funds for some specific styles. To ensure that our result is robust to alternative distress definitions, other style classifications are applied. First, we use broad CRSP investment styles defined as the first 2 digits of CRSP style code. The broad investment styles represent more general asset classes and thus increase number of funds in each style.

Table 3.9 presents the effect of Interfund Lending Programs (ILPs) on fund returns following distress defined using board investment styles. We find that effectiveness of Interfund Lending Programs for borrowing funds remain qualitatively the same, as shown by positive and significant interaction term Distress×ILP in most of the specifications from Column (1)-(5). For distress defined at bottom 0.25th percentile level, the coefficient Distress×ILP amounts to 0.0033 (t-statistics=5.12), indicating that facing extreme negative return shocks, ILP-funds are more resilient than non-ILP funds in obtaining short-term liquidity. We find no effect of Interfund Lending Programs for lending funds.

Second, we use the style classification contained in N-SAR filings. The Item 61-70 in Form N-SAR are check-box survey questions that provide guidelines to create style categories. Specifically, we classify the sample broadly into equity, bond, balanced, and index funds. Within each broad style, we further classify them into sub-categories based on the interactions of N-SAR items, resulting in altogether 24 styles. We repeat the baseline regression using distress defined at N-SAR investment style level.

Table 3.10 shows the result. We confirm the finding in baseline regression that borrowing funds with Interfund Lending Programs have higher returns than non-ILP funds following distress, especially under extreme distress at bottom 0.25th percentile. Column (5) shows that ILP-funds through have 0.22% higher weekly returns, which is highly significant at 1% level. In terms of lending funds, although Column (10) reports significantly positive interaction term, its economic magnitude is very small and thus the effectiveness is limited.

Finally, we define distress events using fixed thresholds instead of relative measures. The idea stems from the proposition that investors only care about absolute fund performance, ignoring the difference among investment styles. Following this argument, we define distress events in the sense that TNA-weighted weekly returns of funds with the same investment style are below -2%, -3%, -4%, -5% and -6%, respectively. The uniform standard of return thresholds applying to all CRSP 4-digit style code leads to large variation in the number of distress funds across styles.

Table 3.11 shows that the effect of Interfund Lending Programs for borrowing funds remains quantitatively similar, as indicated by positive and significant interaction term Distress×ILP under alternative absolute return thresholds. In particular, ILP-funds have 0.07%-0.17% higher returns than non-LIP funds in the week following distress events, with t-statistics all over 2. In contrast, we find no positive effect of Interfund Lending Programs for lending funds in general, as ILP-funds' returns are not significantly different from non-ILP funds if there are other distressed funds in the families.

Excluding Financial Crisis

Figure 3.1 shows that the number of distressed funds peaks around 2008-2009 financial crisis. For example, when distress events are defined under extreme condition, i.e. bottom 0.25th percentile, over 70% of the distress funds are clustered in September 2008. Therefore, our primary result might be driven by distress events during specific sample period. To alleviate this concern, we re-examine the baseline results by excluding observations from 2008-2009.

Table 3.12 reports the result of robustness check with non-crisis period. The baseline result remains intact when we exclude observations during financial crisis. Specifically, on the borrowing side, the funds with Interfund lending Programs have 0.19% and 0.41% higher returns than non-ILP funds under severe distress, defined at bottom 0.5th and 0.25th percentile in Column (4)-(5), respectively. The interaction term Distress×ILP is highly significant with t-statistics greater than 2. The robustness check confirms that the baseline finding is not driven by distress events concentrated during financial crisis period. On the lending side, we find no evidence concerning the effectiveness of Interfund Lending Programs for lending funds.

ILP Application

In our empirical analysis we construct ILP indicator using the date of SEC exemptive order for Interfund Lending Programs. After submitting applications to the SEC, the regular procedure for obtaining approval of Interfund Lending Programs involves several rounds of hearings if necessary. Finally SEC will issue an exemptive order to approve the application. After that, fund families are eligible to use Interfund Lending Programs to mitigate liquidity constraints for some of the affiliated funds. Therefore, there is time interval between application and final approval. We check the robustness of our baseline result using the application date, since the approval date is not fully available prior to 2008. To account for the missing approval date before 2008, we instead construct ILP indicator using the application date and repeat the regression regression.

Table 3.13 presents the result of robustness check when application date of Interfund Lending Programs is used to construct ILP indicator. We find that our result for borrowing funds remains quantitatively similar. In particular, for distress events defined under extreme conditions, the funds with Interfund

Lending Programs have significantly higher returns than non-ILP funds. The economic magnitude increases from 0.05% to 0.33% of returns in the week immediately following distress events. The t-statistics also increases from 1.62 to nearly 5.64, indicating high statistical significance for the interaction terms under various distress definitions. However, similar to previous findings, we find no strong empirical evidence for the effectiveness of Interfund Lending Programs for lenders within fund families.

Additional Controls

In this robustness check we further include several fund characteristics as controls in the regression. The control variables include lagged fund return in the past two weeks, fund TNA, fund age, and expense ratio. These controls have been widely used in the mutual fund literature.

Table 3.14 shows the result of robustness check controlling for additional fund characteristics. We find that our main findings remain intact by introducing additional controls. On one hand, ILP-funds have significantly higher returns than non-ILP funds in the week following distress. For example, Column (5) shows a coefficient of 0.28% for interaction term Distress×ILP (t-statistics=3.62) when distress events are defined at bottom 0.25th percentile level. It indicates that the effectiveness of Interfund Lending Programs remain economically sizable and statistically significant for borrowing funds. On the other hand, we find no evidence supporting the positive role of Interfund Lending Programs for lending funds, as the interaction term Distress×ILP remains insignificant, or even negative under alternative distress definitions.

3.4 Further Discussions

3.4.1 Comparison of Alternative Borrowing Channels

There are multiple channels for mutual funds to get short-term liquidity to meet redemption needs. They could either borrow internally from peer funds within the fund families through Interfund Lending Programs, or borrow externally from banks / other financial institutions, or both at the same time. Disentangling multiple borrowing channels and examine their effectiveness requires empirical work. Therefore, we estimate the following regression to compare the effectiveness of the two borrowing channels:

$$
\begin{aligned}
r_{i,j,k,t+1} =& \beta_1 \text{Distress}_{k,t} \times \text{ILP}_{j,t} + \beta_2 \text{Distress}_{k,t} \times \text{External Borrowing}_{i,t} + \gamma_1 \text{ILP}_{j,t} \\
&+ \gamma_2 \text{External Borrowing}_{i,t} + \theta_i + \delta_{k,t} + \epsilon_{i,t}
\end{aligned} \tag{3.3}
$$

where $\text{ILP}_{j,t}$ is a dummy variable equals one for the time period after SEC exemptive order of Interfund Lending Program for fund family j, and External $\text{Borrowing}_{i,t}$ is a dummy variable equals one if funds have any amount of bank overdraft / bank loan, or engaged in money borrowing activities in year t.

Figure 3.2 presents the external borrowing activities. Panel A reports the number of external borrowing funds that are in distress from 1998-2014. The distress event is defined using bottom 0.25th percentile return threshold. It shows that the frequency distribution of external borrowing funds is quite similar to that of distressed funds in Figure 3.1. Most of the external borrowing activities are concentrated during 2008 financial crisis. Panel B of Figure 3.2 reports the number of distressed funds and external borrowing funds among them for each broad investment style. The broad investment styles are defined using the first 2 digits of CRSP investment style code. About 1/4-1/2 of distressed funds engage in external borrowing activities during the whole sample period. The information in Figure 3.2 demonstrates that mutual funds generally have multiple ways to acquire short-term liquidity.

Table 3.16 compare the effect of Interfund Lending Programs and external borrowing on fund returns following exogenous negative return shocks. The result shows that both sources of funding are effective in providing emergent liquidity to distressed funds. Specifically, the variables of interest Distress×ILP and Distress×External Borrowing in Column (3)-(5) are both positive and highly significant when distress is defined below bottom 1th percentile. Moreover, the economic magnitude of Distress×ILP (0.0033) is almost twice of Distress×External Borrowing (0.0017) under extreme distress, both are highly significant at 1% level. In sum, the comparison of alternative funding sources-interfund lending facilities and external borrowing-suggests that both channels are effective in providing short-term liquidity to distressed funds and reducing adverse price impact following distress. Evidence also indicates that Interfund Lending Programs have larger impact on fund returns following distress events.

3.4.2 Liquidity Management and External Borrowing Needs

The Interfund Lending Programs provide short-term liquidity to the borrowing funds when they are in distress. Chernenko and Sunderam (2016), Zeng (2017) and Ben-Rephael (2017) show that mutual funds engage in substantial liquidity management. They hold substantial amounts of cash, which is used to accommodate redemption requests rather than transacting in the underlying portfolio assets. If cash reserve is not sufficient, then part of portfolio holdings must be liquidated to meet potential redemption needs following distress. With the existence of the Interfund Lending Program, distressed funds could obtain necessary liquidity beyond their cash reserves. Another possible funding channel is to borrow externally from banks or other financial institutions. Usually they obtain credit line from banks for emergency purpose. Therefore, Interfund Lending Programs facilitate liquidity management for the borrowing funds. We hypothesize that there will be smaller magnitude of change in cash reserve for ILP-funds than non-ILP funds following distress events. Similarly, due to less demand for short-term liquidity, borrowing funds with Interfund Lending Programs are also less likely to borrower externally from banks or other sources.

To test these two hypotheses, we construct a panel dataset with fund-year observations from 1998-2015, and estimate the following regressions:

$$\begin{aligned} \Delta Cash_{i,j,k,t} &= \beta \text{Distress}_{k,t} \times \text{ILP}_{j,t} + \gamma \text{ILP}_{j,t} + \theta_i + \delta_t + \epsilon_{i,t} \\ ExternalBorrowing_{i,j,k,t} &= \beta \text{Distress}_{k,t} \times \text{ILP}_{j,t} + \gamma \text{ILP}_{j,t} + \theta_i + \delta_t + \epsilon_{i,t} \end{aligned} \tag{3.4}$$

where $\Delta\text{Cash}_{i,j,k,t}$ is the change of cash holding of fund i in fund family j with investment objective k from year $t-1$ to year t. The cash holding is calculated as sum of cash (N-SAR Item 74-A and 74-B), short-term debt (N-SAR Item 74-C) and other investments (N-SAR Item 74-I) over TNA in year t. $\text{ExternalBorrowing}_{i,j,k,t}$ is an indicator which equals one if the fund has overdrafts (N-SAR Item 55-A) or bank loans (N-SAR Item 55-B) in year t. Distress indicator $\text{Distress}_{k,t}$ is a dummy variable equals one if funds with investment style k is in distress in year t. Funds with investment style k is in distress if the TNA-weighted average weekly returns are below the bottom 3rd, 2nd, 1th, 0.5th and 0.25th percentile within the same investment style during the entire sample period. ILP indicator $\text{ILP}_{j,t}$ is a dummy variable equals one for the time period after SEC exemptive order of ILP for fund family j. The investment styles are based on CRSP 4-digit investment style code.

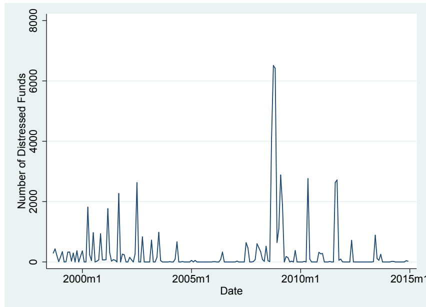
Table 3.15 presents the implication of Interfund Lending Programs for liquidity management and external borrowing. The change in cash holdings are larger for borrowing funds with Interfund Lending Programs than non-ILP funds in the year following distress events. On average, borrowing funds with Interfund Lending Programs have 1.28% higher change in cash positions under extreme distress defined at bottom 0.25th percentile, with t-statistics above 3. The coefficient could be interpreted as suffering less from the reduction in cash positions with Interfund Lending Programs, as it provides additional liquidity to meet the potential outflows following distress. It suggests that funds with Interfund Lending Programs are less likely to dispose their cash reserves, and therefore larger changes in cash positions (may be smaller in absolute magnitude). This is consistent with the expectation that Interfund Lending Programs play significant role in liquidity management for the borrowing funds in distress.

In terms of external borrowing behavior, I find that borrowing funds with Interfund Lending Programs are significantly less likely to engage in external borrowing from banks or other sources than non-ILP funds under some specifications. For instance, borrowing funds with Interfund Lending Programs is associated with 3% smaller probability of external borrowing. The effect is s-tatistically significant at 1% level for distress events defined at bottom 1th and 0.5th percentile of all weekly returns for funds with specific investment style.

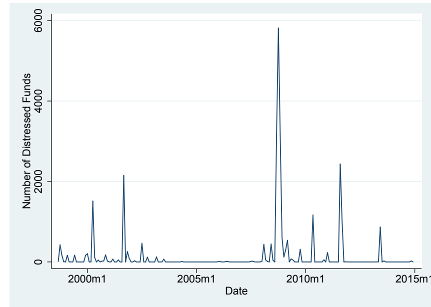
3.5 Conclusion

The Interfund Lending Program is one of the most important lending facilities for mutual funds to as cushion extreme fund outflows. The mechanism allows funds facing large redemption pressure to obtain short-term liquidity from other funds within family, thus alleviating adverse price movement due to asset fire sales. The effectiveness of Interfund Lending Programs for distressed funds lies in the flexibility of lending arrangement and lower-than-market loan rate. The Interfund Lending Programs create an efficient internal capital market for mutual funds and offers an convenient channel for short-term lending facility.

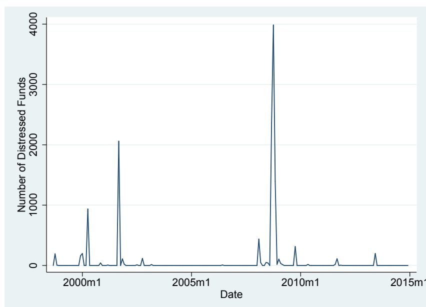
Our paper examines the effectiveness of Interfund Lending Programs for borrowing and lending parties in fund families. We consider how Interfund Lending Programs affect fund returns following distress, measured by extremely low returns for a particular investment style. This kind of distress can be regarded as exogenous shock to the fund flows, possibly leading to liquidity shortage. As a consequence, such distress would trigger interfund lending activities for funds eligible for the Interfund Lending Programs. We are especially interested in the difference in short-term returns between ILP-funds and non-ILP funds following the distress. Overall, we find strong empirical evidences in support of the effectiveness of Interfund Lending Programs for borrowing funds. In general funds eligible for Interfund Lending Programs have 0.32% higher returns in the week following the distress, and the positive effect is persistent for at least two months. In addition, we show that the positive effect for distressed funds are pronounced when the credit market liquidity is low, if they belong to fund families with diversified investment styles, and if fund managers are cooperative in the families. However, we find limited, if any, evidence concerning the effectiveness of Interfund Lending Programs for lending parties. Our primary findings are robust to alternative variable definitions, sample period and model specification. Moreover, we demonstrate that Interfund Lending Programs facilitate liquidity management and reduced external borrowing needs. Overall, our paper highlights the positive role of Interfund Lending Programs in liquidity provision and internal capital market in fund families.



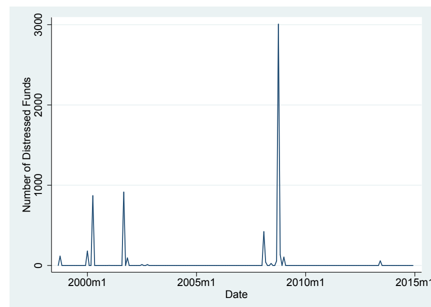
(a) Bottom 2%



(b) Bottom 1%



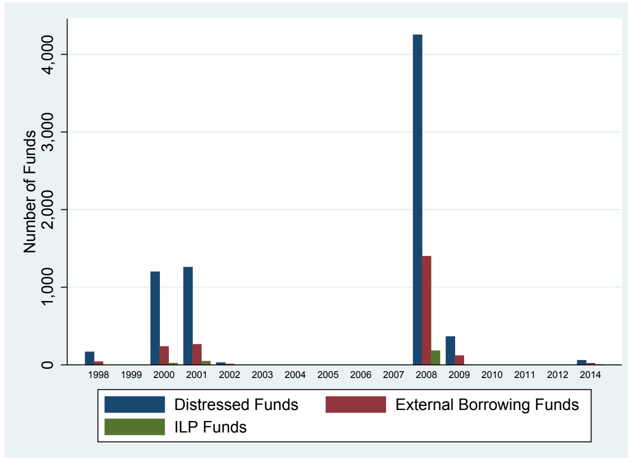
(c) Bottom 0.5%



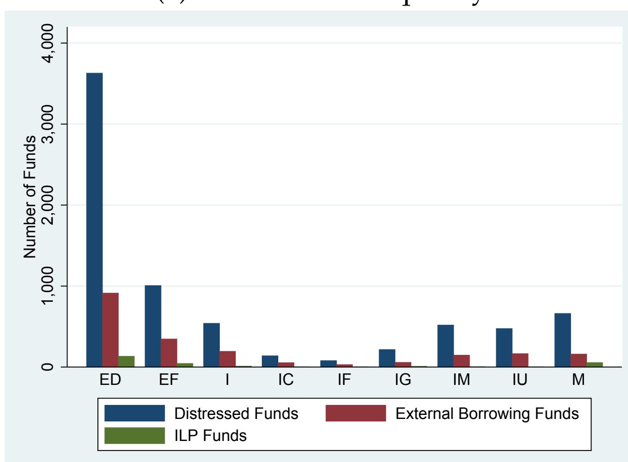
(d) Bottom 0.25%

Figure 3.1: Number of Distressed Funds

This figure reports the number of distressed funds under alternative distress definitions. The distress is defined in the sense that the TNA-weighted weekly returns of funds with the same investment objective are below the bottom 2nd, 1th, 0.5th and 0.25th percentile of the same funds' weekly returns during the whole sample period.



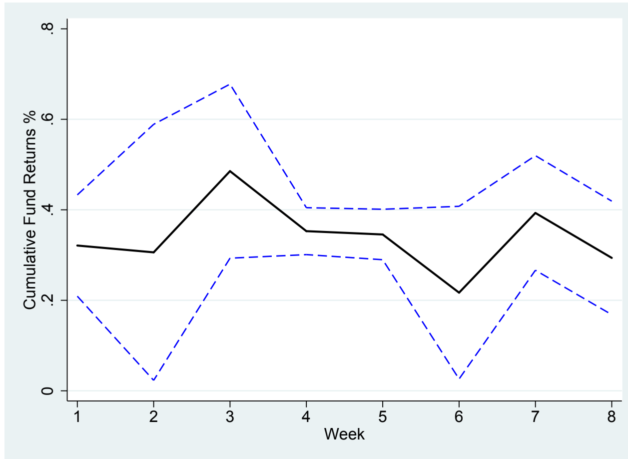
(a) Time-Series Frequency



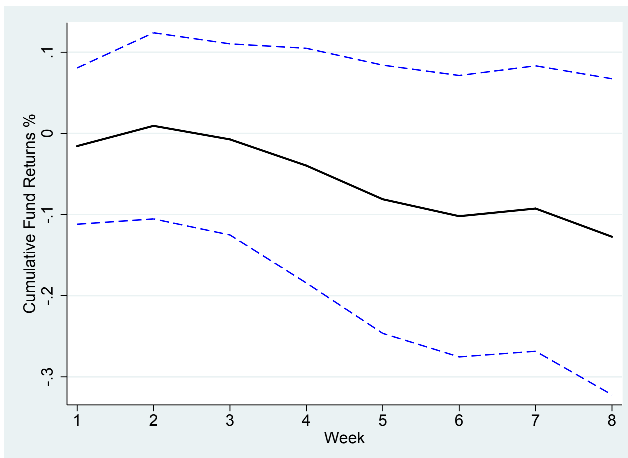
(b) Broad Investment Styles

Figure 3.2: Number of ILP and External Borrowing Funds in Distress

This figure describes external borrowing activities. Panel A reports the number of distressed funds that utilize ILP or borrow externally from 1998-2014. Panel B reports the aggregate numbers for each broad investment style. Mutual funds' actual utilization of Interfund lending Programs are obtained from N-CSR and N-30D filings. ILP funds are defined as having borrowed through Interfund lending Program in year t. External borrowing activities are defined as having any amount of bank overdraft (N-SAR Item 55-A) / bank loan (N-SAR Item 55-B), or engaged in borrowing activities (N-SAR Item 77-O) in year t. We use bottom 0.25th percentile return threshold in the definition of distress. Broad investment styles include domestic equity (ED), foreign equity (EF), general fixed income (I), corporate bond (IC), foreign fixed income (IF), government bond (IG), money market (IM), municipal bond (IU) and balanced (M).



(a) Borrower



(b) Lender

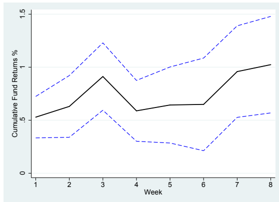
Figure 3.3: Effectiveness of Interfund Lending Programs

This figure reports coefficient of interaction term Distress×ILP (solid) and its 95% confidence interval (dash) in the baseline regression:

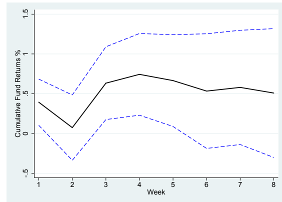
$$\sum_{t=1}^{T} r_{i,j,k,T} = \beta \text{Distress}_{k,t} \times \text{ILP}_{j,t} + \gamma \text{ILP}_{j,t} + \theta_i + \delta_{k,t} + \epsilon_{i,t} \quad T = 1, 2, ...8$$

$$\sum_{t=1}^{T} r_{i,j,k,T} = \beta \text{Distress}_{\cancel{k},j,t} \times \text{ILP}_{j,t} + \gamma \text{ILP}_{j,t} + \theta_i + \delta_{k,t} + \epsilon_{i,t} \quad T = 1, 2, ...8$$

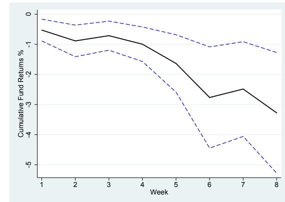
The dependent variable is the cumulative fund returns from week $t+1$ up to $t+8$, where $t = 0$ stands for distress week. The robust standard errors are clustered by fund family and time.



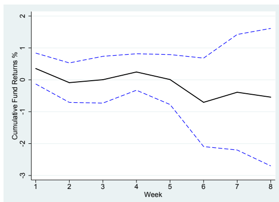
(a) ED



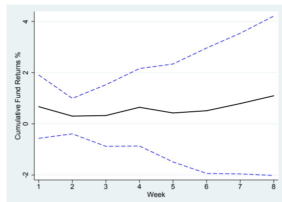
(b) EF



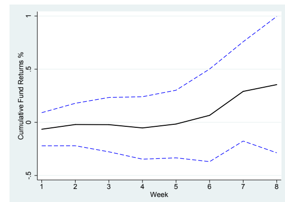
(c) I



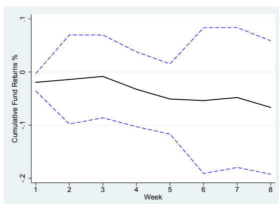
(d) IC



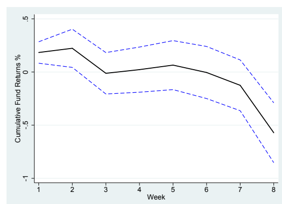
(e) IF



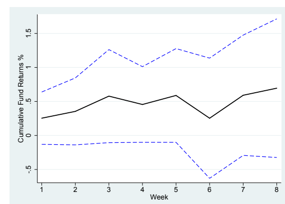
(f) IG



(g) IM



(h) IU



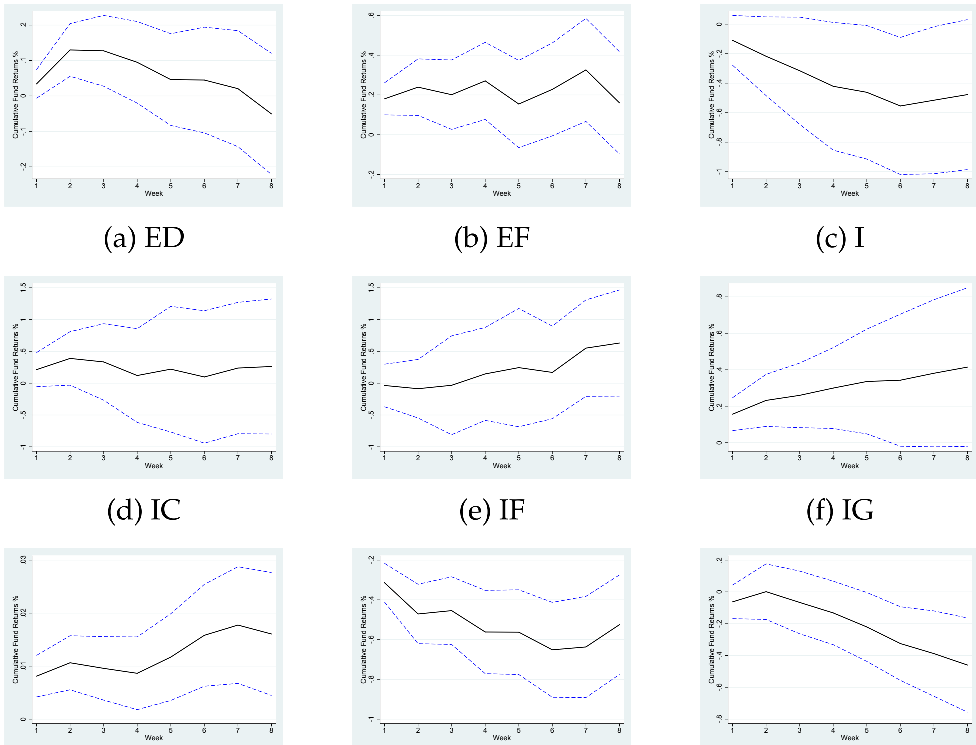
(i) M

Figure 3.4: Effectiveness of Interfund Lending Programs for Borrowers

This figure reports coefficient of interaction term Distress×ILP (solid) and its 95% confidence interval (dash) in the following regression for each broad investment style.

$$\sum_{t=1}^{T} r_{i,j,k,T} = \beta \text{Distress}_{k,t} \times \text{ILP}_{j,t} + \gamma \text{ILP}_{j,t} + \theta_i + \delta_{k,t} + \epsilon_{i,t} \quad T = 1, 2, ...8$$

The dependent variable is the cumulative fund returns from week $t+1$ up to $t+8$, where $t = 0$ stands for distress week. We repeat the regression analysis for each board investment style using the first 2 digits of CRSP investment style code. They include domestic equity (ED), foreign equity (EF), general fixed income (I), corporate bond (IC), foreign fixed income (IF), government bond (IG), money market (IM), municipal bond (IU) and balanced (M). The robust standard errors are clustered by fund.



(a) ED (b) EF (c) I

(d) IC (e) IF (f) IG

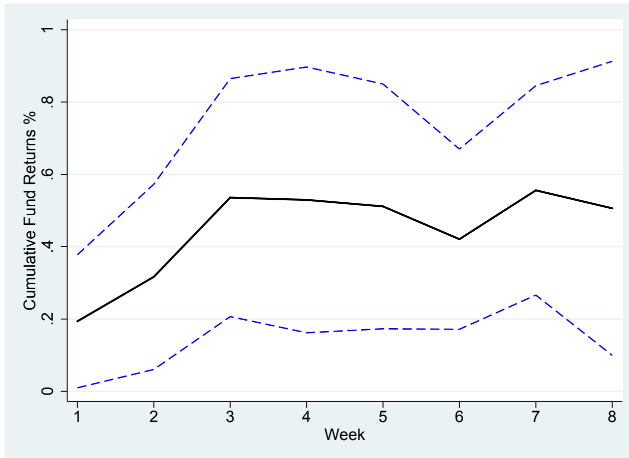
(g) IM (h) IU (i) M

Figure 3.5: Effectiveness of Interfund Lending Programs for Lenders

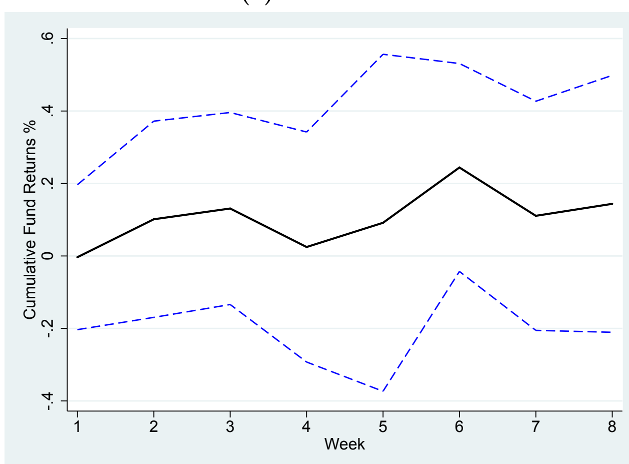
This figure reports coefficient of interaction term Distress×ILP (solid) and its 95% confidence interval (dash) in the following regression for each broad investment style.

$$\sum_{t=1}^{T} r_{i,j,k,T} = \beta \text{Distress}_{k,j,t} \times \text{ILP}_{j,t} + \gamma \text{ILP}_{j,t} + \theta_i + \delta_{k,t} + \epsilon_{i,t} \quad T = 1, 2, ...8$$

The dependent variable is the cumulative fund returns from week $t+1$ up to $t+8$, where $t=0$ stands for distress week. We repeat the regression analysis for each board investment style using the first 2 digits of CRSP investment style code. They include domestic equity (ED), foreign equity (EF), general fixed income (I), corporate bond (IC), foreign fixed income (IF), government bond (IG), money market (IM), municipal bond (IU) and balanced (M). The robust standard errors are clustered by fund.



(a) Borrower



(b) Lender

Figure 3.6: Effectiveness of ILP for Matched Sample

This figure reports coefficient of interaction term Distress×ILP (solid) and its 95% confidence interval (dash) in the baseline regression for the matched sample. The matching is based on investment style, fund size, fund age, expense ratio, front-end load, redemption fee and past two weeks' return prior to the third week of September 2008.

$$\sum_{t=1}^{T} r_{i,j,k,T} = \beta \text{Distress}_{k,t} \times \text{ILP}_{j,t} + \gamma \text{ILP}_{j,t} + \theta_i + \delta_{k,t} + \epsilon_{i,t} \quad T = 1, 2, ...8$$

$$\sum_{t=1}^{T} r_{i,j,k,T} = \beta \text{Distress}_{\not{k},j,t} \times \text{ILP}_{j,t} + \gamma \text{ILP}_{j,t} + \theta_i + \delta_{k,t} + \epsilon_{i,t} \quad T = 1, 2, ...8$$

The dependent variable is the cumulative fund returns from week $t+1$ up to $t+8$, where $t = 0$ stands for distress week.

The robust standard errors are clustered by fund family and time.

Table 3.1: Style-Wide Distress Events

This table presents the summary statistics of style-wide distress events. Distress is defined in the sense that the TNA-weighted weekly returns of funds with the same investment style are below the bottom 0.5th percentile of the same funds' weekly returns during the whole sample period. Probability is the proportion of observations of distressed funds in total number of funds with the same investment style. Mean, Median, Q10 and Q90 are distribution of weekly returns of distressed funds. Detailed information for style classification is provided in Appendix A.11.

CRSP Style Code	Obv	Probability	No. of Distressed Funds	Mean	Median	Q10	Q90
EDCI	11998	0.006	76	-0.142	-0.137	-0.189	-0.106
EDCL	33942	0.004	143	-0.129	-0.115	-0.195	-0.092
EDCM	128362	0.005	579	-0.171	-0.164	-0.234	-0.124
EDCS	195081	0.005	942	-0.163	-0.154	-0.227	-0.117
EDSA	3562	0.006	20	-0.186	-0.19	-0.227	-0.137
EDSC	3152	0.001	3	-0.18	-0.18	-0.18	-0.18
EDSF	13642	0.004	60	-0.162	-0.164	-0.191	-0.13
EDSG	9220	0.004	39	-0.178	-0.164	-0.229	-0.155
EDSH	19699	0.004	70	-0.13	-0.112	-0.189	-0.106
EDSI	1752	0.003	6	-0.136	-0.136	-0.136	-0.136
EDSM	594	0.002	1	-0.16	-0.16	-0.16	-0.16
EDSN	15918	0.003	55	-0.205	-0.185	-0.306	-0.144
EDSR	38537	0.006	218	-0.166	-0.169	-0.183	-0.144
EDSS	1982	0.003	6	-0.185	-0.185	-0.185	-0.185
EDST	28400	0.005	145	-0.184	-0.16	-0.279	-0.138
EDSU	13942	0.005	67	-0.13	-0.102	-0.23	-0.085
EDYB	241263	0.004	1078	-0.119	-0.101	-0.188	-0.085
EDYG	414880	0.004	1834	-0.143	-0.142	-0.179	-0.109
EDYH	11992	0.004	44	-0.058	-0.058	-0.075	-0.04
EDYI	55514	0.005	286	-0.123	-0.102	-0.199	-0.09
EDYS	778	0.003	2	-0.103	-0.103	-0.103	-0.102
EF	230005	0.005	1150	-0.127	-0.111	-0.191	-0.097
EFCS	25505	0.005	131	-0.134	-0.121	-0.183	-0.108
EFRE	20652	0.005	104	-0.141	-0.132	-0.191	-0.106
EFRI	816	0.005	4	-0.082	-0.082	-0.082	-0.082
EFRJ	7266	0.006	40	-0.123	-0.115	-0.17	-0.094
EFRL	5950	0.005	29	-0.22	-0.201	-0.311	-0.165
EFRM	47312	0.005	225	-0.161	-0.156	-0.216	-0.118
EFRP	8134	0.006	50	-0.125	-0.106	-0.208	-0.08
EFRQ	5105	0.005	25	-0.136	-0.138	-0.152	-0.115
EFRX	10251	0.005	49	-0.141	-0.145	-0.17	-0.104
EFSF	849	0.005	4	-0.146	-0.146	-0.146	-0.146
EFSH	1938	0.005	10	-0.19	-0.19	-0.19	-0.19
EFSN	5379	0.003	16	-0.269	-0.269	-0.269	-0.269
EFSR	5999	0.002	11	-0.185	-0.185	-0.185	-0.185
EFST	1827	0.007	13	-0.138	-0.138	-0.138	-0.138
I	246928	0.004	984	-0.03	-0.027	-0.039	-0.025
ICQH	30299	0.002	67	-0.032	-0.029	-0.037	-0.028
ICQY	31097	0.003	99	-0.04	-0.031	-0.07	-0.028
IF	54073	0.005	278	-0.034	-0.032	-0.043	-0.029
IFM	659	0.003	2	0	0	0	0
IG	30212	0.004	125	-0.023	-0.022	-0.028	-0.021
IGD	9253	0.005	43	-0.016	-0.016	-0.018	-0.013
IGDI	13872	0.005	63	-0.019	-0.018	-0.023	-0.017
IGDS	21244	0.003	66	-0.011	-0.011	-0.012	-0.01
IGT	13015	0.005	66	-0.045	-0.042	-0.061	-0.037
IM	236534	0.003	726	0	0	-0.001	0
IU	264530	0.005	1323	-0.037	-0.034	-0.052	-0.03
IUI	62189	0.005	309	-0.021	-0.022	-0.022	-0.02
IUS	12012	0.005	57	-0.005	-0.005	-0.006	-0.004
M	231161	0.005	1115	-0.083	-0.07	-0.135	-0.056
MT	3925	0.005	20	-0.044	-0.039	-0.067	-0.027
OC	765	0.004	3	-0.036	-0.036	-0.036	-0.036
OM	38222	0.004	156	-0.018	-0.015	-0.026	-0.015

Table 3.2: Summary Statistics

This table reports summary statistics for the main variables. The sample consists of fund-week observations from 1998 to 2014. ILP is a dummy variable equals one if the fund family are eligible for Interfund Lending Programs in month *t*, and zero otherwise. Fund Return is calculated as TNA-weighted weekly returns for funds with the same CRSP investment style. Fund TNA is log of fund's total net assets. Fund Age is log of years since fund's inception in N-SAR filings. Expense Ratio is the percentage of total expenses (N-SAR Item 72-X) over total net assets. Front-End Load is percentage of total front-end sales loads collected from sales over total net assets. Redemption Fee is percentage of total amount deferred or contingent deferred sales loads and redemption fees over total net assets. Investment style variables are first 2 digits of CRSP investment style code. Detailed variable definitions are provided in Appendix A.9.

	N	Mean	S.D.	Q10	Q25	Median	Q75	Q90
ILP	2982445	0.27	0.45	0.00	0.00	0.00	1.00	1.00
Fund Return %	2981967	0.12	2.21	-2.02	-0.46	0.08	0.87	2.30
Fund TNA (Billion)	2798874	1.85	6.41	0.02	0.08	0.28	1.06	3.77
Fund Age	2982445	5.35	3.67	2.00	2.00	4.00	7.00	11.00
Expense Ratio %	2798874	1.14	0.95	0.37	0.67	0.97	1.34	1.92
Front-End Load %	2798874	0.05	0.12	0.00	0.00	0.00	0.03	0.15
Redemption Fee %	2798874	0.01	0.03	0.00	0.00	0.00	0.01	0.03
Equity: Domestic	2982445	0.42	0.49	0.00	0.00	0.00	1.00	1.00
Equity: Foreign	2982445	0.13	0.33	0.00	0.00	0.00	0.00	1.00
Fixed Income: General	2982445	0.08	0.28	0.00	0.00	0.00	0.00	0.00
Fixed Income: Corporate	2982445	0.02	0.14	0.00	0.00	0.00	0.00	0.00
Fixed Income: Foreign	2982445	0.02	0.13	0.00	0.00	0.00	0.00	0.00
Fixed Income: Government	2982445	0.03	0.17	0.00	0.00	0.00	0.00	0.00
Fixed Income: Money Market	2982445	0.10	0.30	0.00	0.00	0.00	0.00	0.00
Fixed Income: Municipal	2982445	0.11	0.32	0.00	0.00	0.00	0.00	1.00
Balanced	2982445	0.08	0.27	0.00	0.00	0.00	0.00	0.00
Mortgage-Backed	2982445	0.01	0.11	0.00	0.00	0.00	0.00	0.00

Table 3.3: Effectiveness of Interfund Lending Programs: Baseline Regression

This table presents the effect of Interfund Lending Programs (ILPs) on fund returns following exogenous negative return shocks. The sample consists of fund-week observations from 1998 to 2014. Specifically, we estimate the following two regressions:

$$r_{i,j,k,t+1} = \beta \text{Distress}_{k,t} \times \text{ILP}_{j,t} + \gamma \text{ILP}_{j,t} + \theta_i + \delta_{k,t} + \epsilon_{i,t}$$
$$r_{i,j,k,t+1} = \beta \text{Distress}_{\not{k},j,t} \times \text{ILP}_{j,t} + \gamma \text{ILP}_{j,t} + \theta_i + \delta_{k,t} + \epsilon_{i,t}$$

where $r_{i,j,k,t+1}$ is the return of fund i, belonging to fund family j with investment objective k in week $t+1$. Distress$_{k,t}$ is a dummy variable equals one if funds with investment style k is in distress in week t. Distress$_{\not{k},j,t}$ is a dummy variable equals one if funds in family j with investment style other than k is in distress in week t. Distress is defined in the sense that the TNA-weighted weekly returns of funds with investment objective k are below the bottom 3rd, 2nd, 1th, 0.5th and 0.25th percentile of the same funds' weekly returns during the whole sample period, respectively. ILP$_{j,t}$ is a dummy variable equals one for the time period after SEC exemptive order of Interfund Lending Program for fund family j. The investment styles are based on CRSP 4-digit investment style code. Detailed variable definitions are provided in Appendix A.9. All regressions include style-time and fund fixed effects. The robust t-statistics clustered by fund family and time are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Borrowers					Lenders				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Distress (Bottom 3%)×ILP	0.0005					-0.0002***				
	(1.63)					(-2.77)				
Distress (Bottom 2%)×ILP		0.0006*					-0.0003***			
		(1.72)					(-2.85)			
Distress (Bottom 1%)×ILP			0.0010*					-0.0005***		
			(1.82)					(-2.70)		
Distress (Bottom 0.5%)×ILP				0.0017**					-0.0002	
				(2.14)					(-0.66)	
Distress (Bottom 0.25%)×ILP					0.0032***					-0.0002
					(5.63)					(-0.32)
ILP	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0001	0.0001	0.0001	0.0001
	(0.84)	(0.90)	(0.95)	(0.98)	(1.00)	(1.61)	(1.50)	(1.48)	(1.18)	(1.15)
Style-Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	2955600	2955600	2955600	2955600	2955600	2955600	2955600	2955600	2955600	2955600
Number of Fund Families	563	563	563	563	563	563	563	563	563	563
Adjusted R^2	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87

Table 3.4: Effectiveness of Interfund Lending Programs by Board Investment Style

This table presents the effect of Interfund Lending Programs (ILPs) on fund returns following exogenous negative return shocks for each board investment style. The sample consists of fund-week observations from 1998 to 2014. Specifically, we estimate the following two regressions:

$$r_{i,j,k,t+1} = \beta \text{Distress}_{k,t} \times \text{ILP}_{j,t} + \gamma \text{ILP}_{j,t} + \theta_i + \delta_{k,t} + \epsilon_{i,t}$$

$$r_{i,j,k,t+1} = \beta \text{Distress}_{\not{k},j,t} \times \text{ILP}_{j,t} + \gamma \text{ILP}_{j,t} + \theta_i + \delta_{k,t} + \epsilon_{i,t}$$

where $r_{i,j,k,t+1}$ is the return of fund i, belonging to fund family j with investment objective k in week $t+1$. $\text{Distress}_{k,t}$ is a dummy variable equals one if funds with investment style k is in distress in week t. $\text{Distress}_{\not{k},j,t}$ is a dummy variable equals one if funds in family j with investment style other than k is in distress in week t. Distress is defined in the sense that the TNA-weighted weekly returns of funds with investment objective k are below the bottom 3rd, 2nd, 1th, 0.5th and 0.25th percentile of the same funds' weekly returns during the whole sample period, respectively. $\text{ILP}_{j,t}$ is a dummy variable equals one for the time period after SEC exemptive order of Interfund Lending Program for fund family j. We repeat the regression analysis for each board investment style using the first 2 digits of CRSP investment style code. They include domestic equity (ED), foreign equity (EF), general fixed income (I), corporate bond (IC), foreign fixed income (IF), government bond (IG), money market (IM), municipal bond (IU) and balanced (M). Detailed variable definitions are provided in Appendix A.9. All regressions include style-time and fund fixed effects. The robust t-statistics clustered by fund are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A. Borrowers	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	ED	EF	I	IC	IF	IG	IM	IU	M
Distress (Bottom 0.25%)×ILP	0.0053***	0.0039***	-0.0053***	0.0035	0.0067	-0.0006	-0.0002**	0.0018***	0.0025
	(5.30)	(2.66)	(-2.86)	(1.44)	(1.07)	(-0.82)	(-2.33)	(3.58)	(1.30)
ILP	0.0001	-0.0001	0.0001	-0.0000	-0.0003	0.0000	-0.0000	0.0000	-0.0001
	(1.53)	(-0.68)	(0.47)	(-0.24)	(-1.33)	(0.12)	(-1.54)	(0.38)	(-0.30)
Style-Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1232304	373920	244588	60921	54049	86895	292874	336545	228988
Number of Funds	5411	1631	1146	291	268	388	1078	1144	1092
Adjusted R^2	0.88	0.90	0.42	0.65	0.48	0.70	0.56	0.84	0.77
Panel B. Lenders	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	ED	EF	I	IC	IF	IG	IM	IU	M
Distress (Bottom 0.25%)×ILP	0.0003*	0.0018***	-0.0011	0.0021	-0.0004	0.0016***	0.0001***	-0.0031***	-0.0006
	(1.65)	(4.39)	(-1.27)	(1.57)	(-0.21)	(3.41)	(4.06)	(-6.32)	(-1.17)
ILP	0.0002	-0.0001	0.0001	-0.0000	-0.0003	-0.0000	-0.0000	0.0000**	-0.0000
	(1.61)	(-0.72)	(0.51)	(-0.33)	(-1.24)	(-0.17)	(-1.62)	(2.04)	(-0.24)
Style-Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1232304	373920	244588	60921	54049	86895	292874	336545	228988
Number of Funds	5411	1631	1146	291	268	388	1078	1144	1092
Adjusted R^2	0.88	0.90	0.42	0.65	0.48	0.70	0.56	0.84	0.77

Table 3.5: Effectiveness of Interfund Lending Programs Conditional on Credit Market Liquidity

This table presents the effect of Interfund Lending Programs (ILPs) on fund returns following exogenous negative return shocks conditional on credit market liquidity. The sample consists of fund-week observations from 1998 to 2014. Specifically, we estimate the following two regressions:

$$r_{i,j,k,t+1} = \beta \text{Distress}_{k,t} \times \text{ILP}_{j,t} + \gamma \text{ILP}_{j,t} + \theta_i + \delta_{k,t} + \epsilon_{i,t}$$
$$r_{i,j,k,t+1} = \beta \text{Distress}_{\not{k},j,t} \times \text{ILP}_{j,t} + \gamma \text{ILP}_{j,t} + \theta_i + \delta_{k,t} + \epsilon_{i,t}$$

where $r_{i,j,k,t+1}$ is the return of fund i, belonging to fund family j with investment objective k in week $t+1$. $\text{Distress}_{k,t}$ is a dummy variable equals one if funds with investment style k is in distress in week t. $\text{Distress}_{\not{k},j,t}$ is a dummy variable equals one if funds in family j with investment style other than k is in distress in week t. Distress is defined in the sense that the TNA-weighted weekly returns of funds with investment objective k are below the bottom 3rd, 2nd, 1th, 0.5th and 0.25th percentile of the same funds' weekly returns during the whole sample period, respectively. $\text{ILP}_{j,t}$ is a dummy variable equals one for the time period after SEC exemptive order of Interfund Lending Program for fund family j. The investment styles are based on CRSP 4-digit investment style code. Illiquid period is defined as time period when TED rate is above the sample median. Detailed variable definitions are provided in Appendix A.9. All regressions include style-time and fund fixed effects. The robust t-statistics clustered by fund family and time are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Borrowers										
	Low TED Rate					High TED Rate				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Distress (Bottom 3%)×ILP	-0.0001					0.0006*				
	(-0.40)					(1.80)				
Distress (Bottom 2%)×ILP		0.0000					0.0007*			
		(0.12)					(1.78)			
Distress (Bottom 1%)×ILP			0.0001					0.0012*		
			(1.04)					(1.87)		
Distress (Bottom 0.5%)×ILP				-0.0011*					0.0017**	
				(-1.65)					(2.18)	
Distress (Bottom 0.25%)×ILP					0.0001					0.0033***
					(0.06)					(5.49)
ILP	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0001	0.0001	0.0001	0.0001
	(0.72)	(0.70)	(0.69)	(0.70)	(0.70)	(1.01)	(1.10)	(1.16)	(1.17)	(1.21)
Style-Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1338175	1338175	1338175	1338175	1338175	1617276	1617276	1617276	1617276	1617276
Number of Fund Families	452	452	452	452	452	559	559	559	559	559
Adjusted R^2	0.88	0.88	0.88	0.88	0.88	0.86	0.86	0.86	0.86	0.86

Panel B: Lenders										
	Liquid Period					Illiquid Period				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Distress (Bottom 3%)×ILP	-0.0001*					-0.0003**				
	(-1.84)					(-2.26)				
Distress (Bottom 2%)×ILP		-0.0002***					-0.0003**			
		(-2.59)					(-2.23)			
Distress (Bottom 1%)×ILP			-0.0004					-0.0006**		
			(-1.50)					(-2.31)		
Distress (Bottom 0.5%)×ILP				-0.0003					-0.0002	
				(-1.21)					(-0.55)	
Distress (Bottom 0.25%)×ILP					-0.0001					-0.0002
					(-0.28)					(-0.30)
ILP	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001**	0.0001*	0.0001*	0.0001	0.0001
	(0.88)	(0.87)	(0.79)	(0.72)	(0.70)	(1.99)	(1.79)	(1.82)	(1.44)	(1.43)
Style-Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1338175	1338175	1338175	1338175	1338175	1617276	1617276	1617276	1617276	1617276
Number of Fund Families	452	452	452	452	452	559	559	559	559	559
Adjusted R^2	0.88	0.88	0.88	0.88	0.88	0.86	0.86	0.86	0.86	0.86

Table 3.6: Effectiveness of Interfund Lending Programs Conditional on Intra-Family Style Diversity

This table presents the effect of Interfund Lending Programs (ILPs) on fund returns following exogenous negative return shocks conditional on intra-family style diversity. The sample consists of fund-week observations from 1998 to 2014. Specifically, we estimate the following two regressions:

$$r_{i,j,k,t+1} = \beta \text{Distress}_{k,t} \times \text{ILP}_{j,t} + \gamma \text{ILP}_{j,t} + \theta_i + \delta_{k,t} + \epsilon_{i,t}$$

$$r_{i,j,k,t+1} = \beta \text{Distress}_{\not{k},j,t} \times \text{ILP}_{j,t} + \gamma \text{ILP}_{j,t} + \theta_i + \delta_{k,t} + \epsilon_{i,t}$$

where $r_{i,j,k,t+1}$ is the return of fund i, belonging to fund family j with investment objective k in week $t+1$. $\text{Distress}_{k,t}$ is a dummy variable equals one if funds with investment style k is in distress in week t. $\text{Distress}_{\not{k},j,t}$ is a dummy variable equals one if funds in family j with investment style other than k is in distress in week t. Distress is defined in the sense that the TNA-weighted weekly returns of funds with investment objective k are below the bottom 3rd, 2nd, 1th, 0.5th and 0.25th percentile of the same funds' weekly returns during the whole sample period, respectively. $\text{ILP}_{j,t}$ is a dummy variable equals one for the time period after SEC exemptive order of Interfund Lending Program for fund family j. The investment styles are based on CRSP 4-digit investment style code. High-diversity fund families are defined as having above-median Herfindahl-Hirschman Index of fund total net assets based on CRSP investment styles, where the HHI is calculated as summation of squared proportion of TNA belonging to the CRSP 4-digit investment style code within families. Detailed variable definitions are provided in Appendix A.9. All regressions include style-time and fund fixed effects. The robust t-statistics clustered by fund family and time are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Borrowers										
	Low Diversity					High Diversity				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Distress (Bottom 3%)×ILP	0.0007					0.0003				
	(1.31)					(0.67)				
Distress (Bottom 2%)×ILP		0.0007					0.0005			
		(1.11)					(1.11)			
Distress (Bottom 1%)×ILP			0.0006					0.0010		
			(0.60)					(1.45)		
Distress (Bottom 0.5%)×ILP				0.0015					0.0017	
				(1.05)					(1.57)	
Distress (Bottom 0.25%)×ILP					0.0025					0.0037***
					(0.85)					(3.89)
ILP	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000
	(-1.01)	(-0.96)	(-0.89)	(-0.92)	(-0.91)	(-0.42)	(-0.46)	(-0.44)	(-0.40)	(-0.41)
Style-Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1477502	1477502	1477502	1477502	1477502	1474516	1474516	1474516	1474516	1474516
Number of Fund Families	546	546	546	546	546	193	193	193	193	193
Adjusted R^2	0.84	0.84	0.84	0.84	0.84	0.90	0.90	0.90	0.90	0.90

Panel B: Lenders										
	Low Diversity					High Diversity				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Distress (Bottom 3%)×ILP	-0.0001					-0.0002**				
	(-1.28)					(-2.34)				
Distress (Bottom 2%)×ILP		-0.0001					-0.0003**			
		(-0.54)					(-2.48)			
Distress (Bottom 1%)×ILP			0.0001					-0.0007***		
			(0.38)					(-2.84)		
Distress (Bottom 0.5%)×ILP				0.0008					-0.0004	
				(1.45)					(-1.20)	
Distress (Bottom 0.25%)×ILP					0.0010**					-0.0003
					(2.52)					(-0.69)
ILP	-0.0000	-0.0001	-0.0001	-0.0001	-0.0001	0.0000	0.0000	0.0000	-0.0000	-0.0000
	(-0.60)	(-0.76)	(-0.85)	(-0.97)	(-0.95)	(0.23)	(0.23)	(0.20)	(-0.12)	(-0.22)
Style-Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1477502	1477502	1477502	1477502	1477502	1474516	1474516	1474516	1474516	1474516
Number of Fund Families	546	546	546	546	546	193	193	193	193	193
Adjusted R^2	0.84	0.84	0.84	0.84	0.84	0.90	0.90	0.90	0.90	0.90

Table 3.7: Competitive VS. Cooperative Fund Managers

This table presents the effect of Interfund Lending Programs (ILPs) on the returns of lending funds with competitive VS. cooperative fund managers following exogenous negative return shocks. The sample consists of fund-week observations from 1998 to 2014. Specifically, we estimate the following regression:

$$r_{i,j,k,t+1} = \beta \text{Distress}_{\not{k},j,t} \times \text{ILP}_{j,t} + \gamma \text{ILP}_{j,t} + \theta_i + \delta_{k,t} + \epsilon_{i,t}$$

where $r_{i,j,k,t+1}$ is the return of fund i, belonging to fund family j with investment objective k in week $t+1$. $\text{Distress}_{k,t-1}$ is a dummy variable equals one if funds with investment style k is in distress in week t. $\text{Distress}_{\not{k},j,t}$ is a dummy variable equals one if funds in family j with investment style other than k is in distress in week t. Distress is defined in the sense that the TNA-weighted weekly returns of funds with investment objective k are below the bottom 3rd, 2nd, 1th, 0.5th and 0.25th percentile of the same funds' weekly returns during the whole sample period, respectively. $\text{ILP}_{j,t}$ is a dummy variable equals one for the time period after SEC exemptive order of Interfund Lending Program for fund family j. The investment styles are based on CRSP 4-digit investment style code. We divide the sample based on competitive and cooperative fund managers. Detailed variable definitions are provided in Appendix A.9. All regressions include style-time and fund fixed effects. The robust t-statistics clustered by fund family and time are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Borrowers										
	Competitive Managers					Cooperative Managers				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Distress (Bottom 3%)×ILP	0.0003					0.0002				
	(0.70)					(1.18)				
Distress (Bottom 2%)×ILP		0.0003					0.0004***			
		(0.58)					(2.68)			
Distress (Bottom 1%)×ILP			0.0004					0.0007***		
			(0.47)					(3.05)		
Distress (Bottom 0.5%)×ILP				0.0008					0.0014***	
				(0.62)					(2.72)	
Distress (Bottom 0.25%)×ILP					0.0014					0.0027***
					(0.78)					(5.37)
ILP	0.0000	0.0000	0.0000	0.0000	0.0000	0.0002**	0.0002**	0.0002**	0.0002**	0.0002**
	(0.49)	(0.52)	(0.55)	(0.55)	(0.56)	(2.43)	(2.43)	(2.49)	(2.50)	(2.52)
Style-Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1371338	1371338	1371338	1371338	1371338	1376922	1376922	1376922	1376922	1376922
Number of Fund Families	451	451	451	451	451	278	278	278	278	278
Adjusted R^2	0.85	0.85	0.85	0.85	0.85	0.89	0.89	0.89	0.89	0.89

Panel B: Lenders										
	Competitive Managers					Cooperative Managers				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Distress (Bottom 3%)×ILP	-0.0003**					-0.0002*				
	(-2.28)					(-1.95)				
Distress (Bottom 2%)×ILP		-0.0004**					-0.0003***			
		(-2.41)					(-2.60)			
Distress (Bottom 1%)×ILP			-0.0006**					-0.0004**		
			(-2.24)					(-2.42)		
Distress (Bottom 0.5%)×ILP				-0.0004					0.0000	
				(-0.79)					(0.00)	
Distress (Bottom 0.25%)×ILP					-0.0005					0.0001
					(-0.60)					(0.15)
ILP	0.0001	0.0001	0.0001	0.0000	0.0000	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***
	(0.99)	(0.90)	(0.83)	(0.67)	(0.64)	(3.02)	(2.95)	(2.82)	(2.60)	(2.67)
Style-Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1371338	1371338	1371338	1371338	1371338	1376922	1376922	1376922	1376922	1376922
Number of Fund Families	451	451	451	451	451	278	278	278	278	278
Adjusted R^2	0.85	0.85	0.85	0.85	0.85	0.89	0.89	0.89	0.89	0.89

Table 3.8: Effectiveness of Interfund Lending Programs around Collapse of Lehman Brothers

This table presents the effect of Interfund Lending Program (ILP) on fund returns around the collapse of Lehman Brothers in September 2008. The sample consists of fund-week observations. Specifically, we estimate the following two regressions for the matched sample:

$$r_{i,j,k,t+1} = \beta \text{Distress}_{k,t} \times \text{ILP}_{j,t} + \gamma \text{ILP}_{j,t} + \theta_i + \delta_{k,t} + \epsilon_{i,t}$$

$$r_{i,j,k,t+1} = \beta \text{Distress}_{\not{k},j,t} \times \text{ILP}_{j,t} + \gamma \text{ILP}_{j,t} + \theta_i + \delta_{k,t} + \epsilon_{i,t}$$

where $r_{i,j,k,t+1}$ is the return of fund i, belonging to fund family j with investment objective k in week $t+1$. $\text{Distress}_{k,t}$ is a dummy variable equals one if funds with investment style k is in distress in week t. $\text{Distress}_{\not{k},j,t}$ is a dummy variable equals one if funds in family j with investment style other than k is in distress in week t. Distress is defined in the sense that the TNA-weighted weekly returns of funds with investment objective k are below the bottom 3rd, 2nd, 1th, 0.5th and 0.25th percentile of the same funds' weekly returns during the whole sample period, respectively. $\text{ILP}_{j,t}$ is a dummy variable equals one for the time period after SEC exemptive order of Interfund Lending Program for fund family j. The investment styles are based on CRSP 4-digit investment style code. Panel A reports result for unmatched sample, while Panel B reports result for matched sample. The matching is based on fund size, fund age, expense ratio, front-end load, redemption fee, past two weeks' return prior to the third week of September 2008, and investment style. Panel C reports result of balance test for covariates before and after the matching. We define include 10 weeks of pre- and post-event period. Detailed variable definitions are provided in Appendix A.9. All regressions include style-time and fund fixed effects. The robust t-statistics clustered by fund family and time are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Unmatched Sample										
	Borrowers					Lenders				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Distress (Bottom 3%)×ILP	0.0015*					-0.0011				
	(1.91)					(-1.62)				
Distress (Bottom 2%)×ILP		0.0018**					-0.0014**			
		(2.18)					(-2.79)			
Distress (Bottom 1%)×ILP			0.0022**					-0.0016***		
			(2.21)					(-3.08)		
Distress (Bottom 0.5%)×ILP				0.0026**					-0.0005	
				(2.12)					(-0.66)	
Distress (Bottom 0.25%)×ILP					0.0035***					-0.0001
					(3.68)					(-0.15)
ILP	0.0025***	0.0025***	0.0026***	0.0027***	0.0029***	0.0029***	0.0030***	0.0032***	0.0030***	0.0030***
	(3.29)	(2.93)	(3.22)	(3.75)	(3.16)	(4.07)	(5.09)	(4.67)	(5.07)	(4.89)
Style-Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	76687	76687	76687	76687	76687	76687	76687	76687	76687	76687
Number of Fund Families	248	248	248	248	248	248	248	248	248	248
Adjusted R^2	0.93	0.93	0.93	0.93	0.93	0.93	0.93	0.93	0.93	0.93

Panel B: Matched Sample										
	Borrowers					Lenders				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Distress (Bottom 3%)×ILP	0.0013*					-0.0010**				
	(2.08)					(-2.12)				
Distress (Bottom 2%)×ILP		0.0014**					-0.0011***			
		(2.10)					(-3.02)			
Distress (Bottom 1%)×ILP			0.0018**					-0.0013**		
			(2.35)					(-2.72)		
Distress (Bottom 0.5%)×ILP				0.0023**					-0.0003	
				(2.37)					(-0.43)	
Distress (Bottom 0.25%)×ILP					0.0019**					-0.0000
					(2.20)					(-0.04)
ILP	0.0030***	0.0030***	0.0031***	0.0031**	0.0033***	0.0033***	0.0033***	0.0035***	0.0034***	0.0034***
	(3.50)	(3.32)	(3.51)	(2.84)	(3.50)	(5.72)	(5.50)	(5.80)	(5.71)	(5.60)
Style FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	36226	36226	36226	36226	36226	36226	36226	36226	36226	36226
Number of Fund Families	185	185	185	185	185	185	185	185	185	185
Adjusted R^2	0.93	0.93	0.93	0.93	0.93	0.93	0.93	0.93	0.93	0.93

Panel C: Balance Test of Covariates					
	Sample	Control	Treatment	Diff	T-stats
Lagged Fund Return	Full	-0.16	-0.16	-0.01	-1.87
	Matched	-0.15	-0.15	0.00	0.87
Ln(Fund TNA)	Full	12.26	13.28	-1.02	-13.94
	Matched	13.09	13.02	0.06	0.73
Ln(Fund Age)	Full	1.43	1.70	-0.27	-9.49
	Matched	1.70	1.62	0.08	2.27
Expense Ratio	Full	1.44	1.08	0.36	10.02
	Matched	1.10	1.14	-0.04	-1.10
Front-End Load	Full	0.05	0.05	0.00	0.86
	Matched	0.06	0.05	0.00	0.72
Redemption Fee	Full	0.01	0.02	-0.00	-3.46
	Matched	0.01	0.01	-0.00	-0.12

Table 3.9: Robustness Checks: Defining Distress Events with Broad CRSP Investment Styles

This table presents the effect of Interfund Lending Programs (ILPs) on fund returns following exogenous negative return shocks. The sample consists of fund-week observations from 1998 to 2014. Specifically, we estimate the following two regressions:

$$r_{i,j,k,t+1} = \beta \text{Distress}_{k,t} \times \text{ILP}_{j,t} + \gamma \text{ILP}_{j,t} + \theta_i + \delta_{k,t} + \epsilon_{i,t}$$

$$r_{i,j,k,t+1} = \beta \text{Distress}_{\not{k},j,t} \times \text{ILP}_{j,t} + \gamma \text{ILP}_{j,t} + \theta_i + \delta_{k,t} + \epsilon_{i,t}$$

where $r_{i,j,k,t+1}$ is the return of fund i, belonging to fund family j with investment objective k in week $t+1$. $\text{Distress}_{k,t}$ is a dummy variable equals one if funds with investment style k is in distress in week t. $\text{Distress}_{\not{k},j,t}$ is a dummy variable equals one if funds in family j with investment style other than k is in distress in week t. Distress is defined in the sense that the TNA-weighted weekly returns of funds with investment objective k are below the bottom 3rd, 2nd, 1th, 0.5th and 0.25th percentile of the same funds' weekly returns during the whole sample period, respectively. $\text{ILP}_{j,t}$ is a dummy variable equals one for the time period after SEC exemptive order of Interfund Lending Program for fund family j. The investment styles are based on the first 2 digits of CRSP investment style code. Detailed variable definitions are provided in Appendix A.9. All regressions include style-time and fund fixed effects. The robust t-statistics clustered by fund family and time are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Borrowers					Lenders				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Distress (Bottom 3%)×ILP	0.0004					-0.0003**				
	(1.59)					(-2.14)				
Distress (Bottom 2%)×ILP		0.0007*					-0.0004***			
		(1.83)					(-2.67)			
Distress (Bottom 1%)×ILP			0.0009*					-0.0009***		
			(1.67)					(-2.99)		
Distress (Bottom 0.5%)×ILP				0.0016*					-0.0005	
				(1.88)					(-1.21)	
Distress (Bottom 0.25%)×ILP					0.0033***					0.0003
					(5.12)					(0.89)
ILP	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0001	0.0001	0.0001	0.0001
	(0.85)	(0.87)	(0.97)	(0.98)	(0.99)	(1.49)	(1.60)	(1.47)	(1.26)	(1.09)
Style-Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	2955600	2955600	2955600	2955600	2955600	2955600	2955600	2955600	2955600	2955600
Number of Fund Families	563	563	563	563	563	563	563	563	563	563
Adjusted R^2	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87

Table 3.10: Robustness Checks: Defining Distress Events with N-SAR Investment Styles

This table presents the effect of Interfund Lending Programs (ILPs) on fund returns following exogenous negative return shocks. The sample consists of fund-week observations from 1998 to 2014. Specifically, we estimate the following two regressions:

$$r_{i,j,k,t+1} = \beta \text{Distress}_{k,t} \times \text{ILP}_{j,t} + \gamma \text{ILP}_{j,t} + \theta_i + \delta_{k,t} + \epsilon_{i,t}$$
$$r_{i,j,k,t+1} = \beta \text{Distress}_{\not{k},j,t} \times \text{ILP}_{j,t} + \gamma \text{ILP}_{j,t} + \theta_i + \delta_{k,t} + \epsilon_{i,t}$$

where $r_{i,j,k,t+1}$ is the return of fund i, belonging to fund family j with investment objective k in week $t+1$. $\text{Distress}_{k,t}$ is a dummy variable equals one if funds with investment style k is in distress in week t. $\text{Distress}_{\not{k},j,t}$ is a dummy variable equals one if funds in family j with investment style other than k is in distress in week t. Distress is defined in the sense that the TNA-weighted weekly returns of funds with investment objective k are below the bottom 3rd, 2nd, 1th, 0.5th and 0.25th percentile of the same funds' weekly returns during the whole sample period, respectively. $\text{ILP}_{j,t}$ is a dummy variable equals one for the time period after SEC exemptive order of Interfund Lending Program for fund family j. The investment styles are based on N-SAR investment style formulated from Item 61-70. Detailed variable definitions are provided in Appendix A.9. All regressions include style-time and fund fixed effects. The robust t-statistics clustered by fund family and time are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Borrowers					Lenders				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Distress (Bottom 3%)×ILP	0.0002					-0.0001				
	(0.54)					(-1.15)				
Distress (Bottom 2%)×ILP		0.0002					-0.0004***			
		(0.44)					(-3.01)			
Distress (Bottom 1%)×ILP			0.0005					-0.0002		
			(0.81)					(-0.68)		
Distress (Bottom 0.5%)×ILP				0.0014					-0.0003	
				(1.58)					(-0.68)	
Distress (Bottom 0.25%)×ILP					0.0022***					0.0009**
					(5.35)					(2.01)
ILP	0.0000	0.0001	0.0001	0.0000	0.0000	0.0001	0.0001	0.0001	0.0001	0.0001
	(0.99)	(1.03)	(1.01)	(1.00)	(1.01)	(1.27)	(1.44)	(1.20)	(1.18)	(1.02)
Style-Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	2955600	2955600	2955600	2955600	2955600	2955600	2955600	2955600	2955600	2955600
Number of Fund Families	563	563	563	563	563	563	563	563	563	563
Adjusted R^2	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87

Table 3.11: Robustness Checks: Defining Distress Events with Fixed Return Thresholds

This table presents the effect of Interfund Lending Programs (ILPs) on fund returns following exogenous negative return shocks. The sample consists of fund-week observations from 1998 to 2014. Specifically, we estimate the following two regressions:

$$r_{i,j,k,t+1} = \beta \text{Distress}_{k,t} \times \text{ILP}_{j,t} + \gamma \text{ILP}_{j,t} + \theta_i + \delta_{k,t} + \epsilon_{i,t}$$
$$r_{i,j,k,t+1} = \beta \text{Distress}_{\not{k},j,t} \times \text{ILP}_{j,t} + \gamma \text{ILP}_{j,t} + \theta_i + \delta_{k,t} + \epsilon_{i,t}$$

where $r_{i,j,k,t+1}$ is the return of fund i, belonging to fund family j with investment objective k in week $t+1$. $\text{Distress}_{k,t}$ is a dummy variable equals one if funds with investment style k is in distress in week t. $\text{Distress}_{\not{k},j,t}$ is a dummy variable equals one if funds in family j with investment style other than k is in distress in week t. Distress is defined in the sense that the TNA-weighted weekly returns of funds with investment objective k are below -2%, -3%, -4%, -5% and -6%, respectively. $\text{ILP}_{j,t}$ is a dummy variable equals one for the time period after SEC exemptive order of Interfund Lending Program for fund family j. The investment styles are based on CRSP 4-digit investment style code. Detailed variable definitions are provided in Appendix A.9. All regressions include style-time and fund fixed effects. The robust t-statistics clustered by fund family and time are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Borrowers					Lenders				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Distress (Below -4%)×ILP	0.0007***					-0.0001				
	(2.69)					(-1.55)				
Distress (Below -5%)×ILP		0.0010***					-0.0001			
		(2.66)					(-1.25)			
Distress (Below -6%)×ILP			0.0013**					-0.0001		
			(2.36)					(-1.06)		
Distress (Below -7%)×ILP				0.0016**					-0.0001	
				(2.36)					(-0.43)	
Distress (Below -8%)×ILP					0.0017**					0.0000
					(2.07)					(0.07)
ILP	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0001	0.0001	0.0001	0.0001
	(0.73)	(0.81)	(0.88)	(0.92)	(0.98)	(1.45)	(1.33)	(1.26)	(1.18)	(1.11)
Style-Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	2955600	2955600	2955600	2955600	2955600	2955600	2955600	2955600	2955600	2955600
Number of Fund Families	563	563	563	563	563	563	563	563	563	563
Adjusted R^2	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87

Table 3.12: Robustness Checks: Excluding Financial Crisis Period

This table presents the effect of Interfund Lending Programs (ILPs) on fund returns following exogenous negative return shocks. The sample consists of fund-week observations from 1998 to 2014, excluding financial crisis period from 2008-2009. Specifically, we estimate the following two regressions:

$$r_{i,j,k,t+1} = \beta \text{Distress}_{k,t} \times \text{ILP}_{j,t} + \gamma \text{ILP}_{j,t} + \theta_i + \delta_{k,t} + \epsilon_{i,t}$$
$$r_{i,j,k,t+1} = \beta \text{Distress}_{\not{k},j,t} \times \text{ILP}_{j,t} + \gamma \text{ILP}_{j,t} + \theta_i + \delta_{k,t} + \epsilon_{i,t}$$

where $r_{i,j,k,t+1}$ is the return of fund i, belonging to fund family j with investment objective k in week $t+1$. $\text{Distress}_{k,t}$ is a dummy variable equals one if funds with investment style k is in distress in week t. $\text{Distress}_{\not{k},j,t}$ is a dummy variable equals one if funds in family j with investment style other than k is in distress in week t. Distress is defined in the sense that the TNA-weighted weekly returns of funds with investment objective k are below the bottom 3rd, 2nd, 1th, 0.5th and 0.25th percentile of the same funds' weekly returns during the whole sample period, respectively. $\text{ILP}_{j,t}$ is a dummy variable equals one for the time period after SEC exemptive order of Interfund Lending Program for fund family j. The investment styles are based on CRSP 4-digit investment style code. Detailed variable definitions are provided in Appendix A.9. All regressions include style-time and fund fixed effects. The robust t-statistics clustered by fund family and time are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Borrowers					Lenders				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Distress (Bottom 3%)×ILP	0.0003					-0.0001				
	(1.39)					(-1.12)				
Distress (Bottom 2%)×ILP		0.0003					-0.0000			
		(1.19)					(-0.83)			
Distress (Bottom 1%)×ILP			0.0007**					-0.0001		
			(2.18)					(-1.55)		
Distress (Bottom 0.5%)×ILP				0.0019***					0.0000	
				(2.74)					(0.24)	
Distress (Bottom 0.25%)×ILP					0.0041***					0.0003
					(10.87)					(1.30)
ILP	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
	(1.34)	(1.41)	(1.41)	(1.43)	(1.43)	(1.60)	(1.49)	(1.53)	(1.47)	(1.45)
Style-Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	2556609	2556609	2556609	2556609	2556609	2556609	2556609	2556609	2556609	2556609
Number of Fund Families	557	557	557	557	557	557	557	557	557	557
Adjusted R^2	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85	0.85

Table 3.13: Robustness Checks: ILP Application

This table presents the effect of Interfund Lending Programs (ILPs) on fund returns following exogenous negative return shocks. The sample consists of fund-week observations from 1998 to 2014. Specifically, we estimate the following two regressions:

$$r_{i,j,k,t+1} = \beta \text{Distress}_{k,t} \times \text{ILP}_{j,t} + \gamma \text{ILP}_{j,t} + \theta_i + \delta_{k,t} + \epsilon_{i,t}$$
$$r_{i,j,k,t+1} = \beta \text{Distress}_{\not{k},j,t} \times \text{ILP}_{j,t} + \gamma \text{ILP}_{j,t} + \theta_i + \delta_{k,t} + \epsilon_{i,t}$$

where $r_{i,j,k,t+1}$ is the return of fund i, belonging to fund family j with investment objective k in week $t+1$. $\text{Distress}_{k,t}$ is a dummy variable equals one if funds with investment style k is in distress in week t. $\text{Distress}_{\not{k},j,t}$ is a dummy variable equals one if funds in family j with investment style other than k is in distress in week t. Distress is defined in the sense that the TNA-weighted weekly returns of funds with investment objective k are below the bottom 3rd, 2nd, 1th, 0.5th and 0.25th percentile of the same funds' weekly returns during the whole sample period, respectively. $\text{ILP}_{j,t}$ is a dummy variable equals one for the time period after application of Interfund Lending Program for fund family j. The investment styles are based on CRSP 4-digit investment style code. Detailed variable definitions are provided in Appendix A.9. All regressions include style-time and fund fixed effects. The robust t-statistics clustered by fund family and time are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Borrowers					Lenders				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Distress (Bottom 3%)×ILP	0.0005					-0.0002**				
	(1.59)					(-2.43)				
Distress (Bottom 2%)×ILP		0.0006					-0.0002**			
		(1.63)					(-2.58)			
Distress (Bottom 1%)×ILP			0.0009*					-0.0005***		
			(1.77)					(-2.67)		
Distress (Bottom 0.5%)×ILP				0.0017**					-0.0002	
				(2.30)					(-0.59)	
Distress (Bottom 0.25%)×ILP					0.0032***					-0.0002
					(5.72)					(-0.34)
ILP	0.0000	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
	(0.87)	(0.93)	(0.97)	(0.99)	(1.02)	(1.59)	(1.52)	(1.54)	(1.20)	(1.17)
Style-Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	2955600	2955600	2955600	2955600	2955600	2955600	2955600	2955600	2955600	2955600
Number of Fund Families	563	563	563	563	563	563	563	563	563	563
Adjusted R^2	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87

Table 3.14: Robustness Checks: Additional Control Variables

This table presents the effect of Interfund Lending Programs (ILPs) on fund returns following exogenous negative return shocks. The sample consists of fund-week observations from 1998 to 2014. Specifically, we estimate the following two regressions:

$$r_{i,j,k,t+1} = \beta \text{Distress}_{k,t} \times \text{ILP}_{j,t} + \gamma \text{ILP}_{j,t} + \eta \text{X}_{i,t} + \theta_i + \delta_{k,t} + \epsilon_{i,t}$$
$$r_{i,j,k,t+1} = \beta \text{Distress}_{\not k,j,t} \times \text{ILP}_{j,t} + \gamma \text{ILP}_{j,t} + \eta \text{X}_{i,t} + \theta_i + \delta_{k,t} + \epsilon_{i,t}$$

where $r_{i,j,k,t+1}$ is the return of fund i, belonging to fund family j with investment objective k in week $t+1$. $\text{Distress}_{k,t}$ is a dummy variable equals one if funds with investment style k is in distress in week t. $\text{Distress}_{\not k,j,t}$ is a dummy variable equals one if funds in family j with investment style other than k is in distress in week t. Distress is defined in the sense that the TNA-weighted weekly returns of funds with investment objective k are below the bottom 3rd, 2nd, 1th, 0.5th and 0.25th percentile of the same funds' weekly returns during the whole sample period, respectively. $\text{ILP}_{j,t}$ is a dummy variable equals one for the time period after SEC exemptive order of Interfund Lending Program for fund family j. Additional control variables include lagged fund return in the past two weeks, fund TNA, fund age, and expense ratio. The investment styles are based on CRSP 4-digit investment style code. The control variables include lagged fund returns, log of fund TNA, log of fund age and expense ratio. All regressions include style-time and fund fixed effects. The robust t-statistics clustered by fund family and time are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Borrowers					Lenders				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Distress (Bottom 3%)×ILP	0.0004*					-0.0002***				
	(1.69)					(-2.82)				
Distress (Bottom 2%)×ILP		0.0005*					-0.0002***			
		(1.69)					(-2.87)			
Distress (Bottom 1%)×ILP			0.0008*					-0.0005***		
			(1.81)					(-2.77)		
Distress (Bottom 0.5%)×ILP				0.0015**					-0.0002	
				(2.05)					(-0.59)	
Distress (Bottom 0.25%)×ILP					0.0028***					-0.0001
					(3.61)					(-0.20)
ILP	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000
	(0.48)	(0.56)	(0.61)	(0.63)	(0.65)	(1.33)	(1.20)	(1.19)	(0.83)	(0.79)
Lagged Fund Return	0.0021	0.0021	0.0021	0.0021	0.0021	0.0021	0.0021	0.0020	0.0021	0.0021
	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.12)	(0.13)	(0.13)
Ln(Fund TNA)	-0.0003***	-0.0003***	-0.0003***	-0.0003***	-0.0003***	-0.0003***	-0.0003***	-0.0003***	-0.0003***	-0.0003***
	(-5.42)	(-5.42)	(-5.42)	(-5.42)	(-5.43)	(-5.43)	(-5.43)	(-5.44)	(-5.43)	(-5.43)
Ln(Fund Age)	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
	(1.18)	(1.18)	(1.18)	(1.18)	(1.18)	(1.23)	(1.23)	(1.25)	(1.21)	(1.20)
Expense Ratio	-0.0003***	-0.0003***	-0.0003***	-0.0003***	-0.0003***	-0.0003***	-0.0003***	-0.0003***	-0.0003***	-0.0003***
	(-6.60)	(-6.60)	(-6.60)	(-6.60)	(-6.60)	(-6.61)	(-6.62)	(-6.62)	(-6.61)	(-6.61)
Style-Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	2759746	2759746	2759746	2759746	2759746	2759746	2759746	2759746	2759746	2759746
Number of Fund Families	557	557	557	557	557	557	557	557	557	557
Adjusted R^2	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87	0.87

Table 3.15: Liquidity Management and External Borrowing

This table presents effect of Interfund Lending Programs (ILPs) for liquidity management and external borrowing. The sample consists of fund-year observations from 1998 to 2014. Specifically, we estimate the following regression:

$$\Delta Cash_{i,j,k,t} = \beta \text{Distress}_{k,t} \times \text{ILP}_{j,t} + \gamma \text{ILP}_{j,t} + \theta_i + \delta_t + \epsilon_{i,t}$$
$$ExternalBorrowing_{i,j,k,t} = \beta \text{Distress}_{k,t} \times \text{ILP}_{j,t} + \gamma \text{ILP}_{j,t} + \delta_{k,t} + \epsilon_{i,t}$$

where $\Delta Cash_{i,j,k,t}$ is the change of cash holding of fund i in fund family j with investment objective k from year $t-1$ to year t. The cash holding is calculated as sum of cash (N-SAR Item 74-A and 74-B), short-term debt (N-SAR Item 74-C) and other investments (N-SAR Item 74-I) over TNA in year t. $ExternalBorrowing_{i,j,k,t}$ is an indicator which equals one if the funds have any amount of bank overdraft (N-SAR Item 55-A) / bank loan (N-SAR Item 55-B), or engaged in borrowing activities (N-SAR Item 77-O) in year t. $\text{Distress}_{k,t}$ is a dummy variable equals one if funds with investment style k is in distress in year t. Distress is defined in the sense that the TNA-weighted weekly returns of funds with investment objective k are below the bottom 3rd, 2nd, 1th, 0.5th and 0.25th percentile of the same funds' weekly returns during the whole sample period, respectively. $\text{ILP}_{j,t}$ is a dummy variable equals one for the time period after SEC exemptive order of Interfund Lending Program for fund family j. The investment styles are based on CRSP 4-digit investment style code. Detailed variable definitions are provided in Appendix A.9. All regressions include style-time fixed effects. The robust t-statistics clustered by fund are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	$\Delta Cash/TNA$					Borrowing				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Distress (Bottom 3%)×ILP	0.0001					-0.0162*				
	(0.04)					(-1.75)				
Distress (Bottom 2%)×ILP		0.0030					-0.0062			
		(1.60)					(-0.70)			
Distress (Bottom 1%)×ILP			0.0071***					-0.0303***		
			(2.91)					(-3.51)		
Distress (Bottom 0.5%)×ILP				0.0093***					-0.0229**	
				(2.60)					(-2.15)	
Distress (Bottom 0.25%)×ILP					0.0128***					-0.0085
					(3.05)					(-0.73)
ILP	-0.0012	-0.0025**	-0.0029***	-0.0023***	-0.0024***	-0.0381***	-0.0439***	-0.0395***	-0.0439***	-0.0457***
	(-1.03)	(-2.29)	(-3.30)	(-2.83)	(-3.01)	(-4.13)	(-5.08)	(-4.82)	(-5.51)	(-5.79)
Style-Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	56777	56777	56777	56777	56777	72704	72704	72704	72704	72704
Number of Funds	10614	10614	10614	10614	10614	12117	12117	12117	12117	12117
Adjusted R^2	0.02	0.02	0.02	0.02	0.02	0.04	0.04	0.04	0.04	0.04

Table 3.16: Comparison Between Interfund Lending Program and External Borrowing

This table compare the effect of Interfund Lending Programs (ILPs) and external borrowing on fund returns following exogenous negative return shocks. The sample consists of fund-week observations from 1998 to 2014. Specifically, we estimate the following regression:

$$r_{i,j,k,t+1} = \beta_1 \text{Distress}_{k,t} \times \text{ILP}_{j,t} + \beta_2 \text{Distress}_{k,t} \times \text{External Borrowing}_{i,t} + \gamma_1 \text{ILP}_{j,t} + \gamma_2 \text{External Borrowing}_{i,t} + \theta_i + \delta_{k,t} + \epsilon_{i,t}$$

where $r_{i,j,k,t+1}$ is the return of fund i, belonging to fund family j with investment objective k in week $t+1$. Distress$_{k,t}$ is a dummy variable equals one if funds with investment style k is in distress in week t. Distress$_{\not k,j,t}$ is a dummy variable equals one if funds in family j with investment style other than k is in distress in week t. Distress is defined in the sense that the TNA-weighted weekly returns of funds with investment objective k are below the bottom 3rd, 2nd, 1th, 0.5th and 0.25th percentile of the same funds' weekly returns during the whole sample period, respectively. ILP$_{j,t}$ is a dummy variable equals one for the time period after SEC exemptive order of Interfund Lending Program for fund family j. External Borrowing$_{i,t}$ is a dummy variable equals one if funds have any amount of bank overdraft / bank loan, or engaged in borrowing activities in year t. The investment styles are based on CRSP 4-digit investment style code. Detailed variable definitions are provided in Appendix A.9. All regressions include style-time and fund fixed effects. The robust t-statistics clustered by fund family and time are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	(1) Bottom 3%	(2) Bottom 2%	(3) Bottom 1%	(4) Bottom 0.5%	(5) Bottom 0.25%
Distress×ILP	0.0005				
	(1.60)				
Distress×External Borrowing	0.0001				
	(0.59)				
Distress×ILP		0.0006*			
		(1.68)			
Distress×External Borrowing		0.0002			
		(0.72)			
Distress×ILP			0.0010*		
			(1.83)		
Distress×External Borrowing			0.0008**		
			(2.13)		
Distress×ILP				0.0017**	
				(2.14)	
Distress×External Borrowing				0.0012**	
				(2.35)	
Distress×ILP					0.0033***
					(5.98)
Distress×External Borrowing					0.0017***
					(5.06)
ILP	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.82)	(0.88)	(0.93)	(0.95)	(0.78)
External Borrowing	0.0000	0.0000	-0.0000	0.0000	0.0000
	(0.10)	(0.08)	(-0.06)	(0.03)	(0.10)
Style-Time FE	Y	Y	Y	Y	Y
Fund FE	Y	Y	Y	Y	Y
Observations	2955600	2955600	2955600	2955600	2955600
Number of Fund Families	563	563	563	563	563
Adjusted R^2	0.87	0.87	0.87	0.87	0.87

APPENDIX A

APPENDIX

Chapter 1

Factor Model-Based Estimates

Our factor-model-based proxies include the expected returns estimated by the CAPM (Eret-CAPM), the 3-factor model (Eret-FF3) (Fama and French (1993)) and the 4-factor model (Eret-FF4) (Carhart (1997)). Specifically, at the end of each month for each firm, the expected monthly return is estimated as

$$\hat{E}_t\left[r_{i,t+1}\right] = r_{f,t+1} + \sum_{j=1}^{J} \hat{\beta}_i \hat{E}_t\left[f_{j,t}\right] \tag{A.1}$$

$\hat{E}_t\left[r_{i,t+1}\right]$ is expected return for $t+1$, $r_{f,t+1}$ is the risk-free rate for $t+1$, $\hat{\beta}_i$ is the factor loadings and $\hat{E}_t\left[f_{j,t}\right]$ is the expected factor premiums at time t, and $J = 1, 3, 4$ according to different model specifications. The factor loadings are estimated through time-series regression using past five years of monthly stock returns. Factor premiums are the means of factor returns over the same five-year period. Finally, the monthly expected returns are compounded into an annual return for a given fiscal year. We obtain monthly factor premiums, $R_M - R_f$, SMB, HML, and UMD from Ken French's data library.

The Implied Cost of Capital

Following Li et al. (2013), we assume that the steady-state earning growth rate after 15 years (g_t) will be a rolling average of annual GDP growth rate: e.g.

$g_t = ICC_t \times b_t$, where b_t is the constant retention ratio after year 15. Given the first two years' forecast earnings (FE), the initial growth rate (g_{t+2}) is given by: $g_{t+2} = \frac{FE_{t+2}}{FE_{t+1}} - 1$. This implies that $g_{t+2} \exp\{g_t^g \times 15\} = g_t$ with g_t^g being the growth rate of growth rate g_{t+2}, which yields $g_t^g = \ln\left(\frac{g_t}{g_{t+2}}\right)/15$. Now we can construct FE_{t+k} for the next 15 years as $FE_{t+k} = FE_{t+2} \times (1 + g_{t+2} \exp\{g_t^g \times (k-2)\})$ for $3 \leq k \leq 16$.

The retention rate is assumed to revert linearly to the constant rate $b_t = \frac{g_t}{ICC_t}$ by year 16. Thus, we have $b_{t+k} = b_{t+1} - \frac{(b_{t+1} - \frac{g_t}{ICC_t})}{15} \times (k-1)$ for $2 \leq k \leq 16$. The initial retention ratio is estimated as b_{t+1} = [1- Cash Dividend$_t$ /Net Income$_t$].

Now we construct the stream of dividends as $D_{t+k} = FE_{t+k} \times (1 - b_{t+k})$ for $1 \leq k \leq 15$. For the terminal value of remaining cash dividends after year 15, we have: $FE_{t+16} \times (1 - b_t)/(ICC_t - g_t)$. Putting all terms together, we estimate ICC-LNS from the following equation.

$$P_t = \sum_{k=1}^{15} \frac{FE_{t+k} \times [1 - b_{t+1} + \frac{(b_{t+1} - \frac{g_t}{ICC_t})}{15} \times (k-1)]}{(1 + ICC_t)^k} + \frac{FE_{t+15} \times (1 - b_t)}{(ICC_t - g_t)(1 + ICC_t)^{15}}. \qquad (A.2)$$

This equation is equivalent to equation (4) in Li et al. (2013).

We consider an alternative model following the Claus and Thomas (2001) approach. For this, we can obtain the initial forecast value of equity as $BE_{t+1} = BE_t + FE_{t+1} \times (1 - b_{t+1})$, where BE_t is the book equity value per share at t. We then obtain ICC-CT based on the economic profit for shareholders as in the following equation:

$$P_t = BE_t + \sum_{k=1}^{5} \frac{FE_{t+k} - ICC_t \times BE_{t+k-1}}{(1 + ICC_t)^k} + \frac{(FE_{t+5} - ICC_t \times BE_{t+4})(1 + g_t)}{(ICC_t - g_t)(1 + ICC_t)^5} \qquad (A.3)$$

where the growth rate after 5 years, g_t, is estimated by inflation rate. The advantage of using the Claus and Thomas (2001) approach relative to the previous approach is that it does not require future payout ratios. However, this approach is sensitive to the estimated growth rate g_t.

As the last approach, we follow the Gebhardt et al. (2001) and estimate ICC-GLS as follows:

$$P_t = BE_t + \sum_{k=1}^{12} \frac{(ROE_{t+k} - ICC_t)BE_{t+k-1}}{(1 + ICC_t)^k} + \frac{(ROE_{t+12} - ICC_t)BE_{t+11}}{ICC_t(1 + ICC_t)^{12}} \quad \text{(A.4)}$$

where ROE_{t+k} is the return on equity at $t + k$ which is assumed to fade linearly to the industry median ROE (based on 10 years of past data for 48 Fama and French industries, excluding firms with losses) by year $t + 12$. The book value of equity is given by $BE_{t+k} = BE_{t+k-1} + FE_{t+k} \times (1 - b_{t+k})$. This approach mitigates the sensitivity of the ICC to the estimated growth rate in the Claus and Thomas (2001) approach.

The sample includes firms with I/B/E/S earnings forecasts for up to five years and a long-term growth forecast. We also require non-missing data for the prior year's book value of equity and earnings. When explicit forecasts are unavailable, we obtain forecasts by projecting the long-term growth rate on the prior year's earnings forecast.

Table A.1: Variable Definitions

Variable	Definitions
Dependent Variables	
$CAPX$	Capital expenditure (CPAX) over beginning-of-year total assets (AT)
$CAPX + R\&D$	Capital expenditure plus R&D (XRD) over beginning-of-year total assets (AT)
$CAPX + R\&D + M\&A$	Capital expenditure plus R&D (XRD) and M&A (AQC) over beginning-of-year total assets (AT)
$Issuance$	Log difference of adjusted shares outstanding between year t and $t-1$, where adjusted shares outstanding is shares outstanding (SHROUT) divided by total factor (CFACSHR).
Explanatory Variables	
$ICC - LNS$	Internel rate of return that equates a stock's current price to the present value of its expected future free cash flows. Following the methodology of Li, Ng, and Swaminathan (2013))
$ICC - GLS$	Following the methogology of Gebhardt et al. (2001))
$ICC - CT$	Following the methogology of Claus and Thomas (2001))
$Eret - CAPM$	Monthly expected returns estimated by CAPM. $Ret^{CAPM}_{i,t+1} = R_{f,t+1} + \hat{\beta}_1 E[Mktrf_t]$. β is the slope coefficient of time-series regression using past five years of monthly stock returns, and $Mktrf$ is the expected factor risk premium calculated as the average value in the past five years.
$Eret - FF3$	Monthly expected returns estimated by Fama-French three-factor model. $Ret^{FF3}_{i,t+1} = R_{f,t+1} + \hat{\beta}_1 E[Mktrf_t] + \hat{\beta}_2 E[SMB_t] + \hat{\beta}_3 E[HML_t]$. β is estimated by past five years of monthly stock return, and $Mktrf$, SMB, HML are the expected factor risk premiums calculated as the average value in the past five years.
$Eret - FF4$	Monthly expected returns estimated by Fama-French-Carhart four-factor model. $Ret^{CAPM}_{i,t+1} = R_{f,t+1} + \hat{\beta}_1 E[SMB_t] + \hat{\beta}_2 E[HML_t] + \hat{\beta}_3 E[HML_t] + \hat{\beta}_4 E[UMD_t]$. β is estimated by past five years of monthly stock return, and $Mktrf$, SMB, HML ,UMD are the expected factor risk premiums calculated as the average value in the past five years.
Q	Total assets (AT) plus market capitalization (CSHO*PRC) minus common equity (CEQ) over total assets (AT)
CF	Income before extraordinary items (IB) + depreciation and amortization (DP) over total assets (AT)
$1 - R^2$	Price nonsynchronicity, calculated as 1-R^2, where R^2 is the R-square of time-series regression of daily stock returns on market and 3-digit SIC industry returns at year t.
$Equity\ Dependence$	Measured by KZ Index, which is calculated as $KZ_{i,t} = -1.002CF_{i,t} - 39.368DIV_{it} - 1.315CASH_{i,t} + 3.139LEV_{i,t}$
FC	Following Hadlock and Pierce (2010), financial constraint is defined as $FC_{i,t} = 0.737 \times \text{Size}_{i,t} + 0.043 \times \text{Size}^2_{i,t} - 0.04 \times \text{Firmage}_{i,t}$.
$Size$	Natural log of total assets (AT)
Lev	[long-term debt (DLTT) + debt in current liabilities(DLC)] / [long-term debt (DLTT) + debt in current liabilities(DLC)+ Stockholders' Equity (SEQ)
Div	Cash dividend (DV) / total assets (AT)
FA	Net plant, property, and equipment (PPENT) / total assets (AT)
$Cash$	Cash and short-term investments (CHE) / total assets (AT)

Table A.2: Erickson & Whited Errors-in-Variables GMM

This table provides estimation results from Errors-in-Variables GMM regressions. The sample consists of US firms from 1985 to 2013. The dependent variable is capital expenditures (CAPX) scaled by beginning-of-year total assets (AT). ICC-LNS, ICC-GLS and ICC-CT are the implied cost of equity estimates following the methods of Li et al. (2013), Claus and Thomas (2001), and Gebhardt et al. (2001), respectively. Eret-CAPM, Eret-FF3, and Eret-FF4 are expected returns based on the CAPM, the FF3M, and the FF4M. All the cost-of-equity proxies are measured at the beginning of the year. Q is Tobin's q at the beginning of the year and CF is concurrent free cash flow. All regressions include year and firm fixed effects. Detailed definitions of variables are provided in Appendix B. We treat Tobin's q and cost-of-equity proxies as misspecified variables, and use fifth-order cumulants as in Erickson et al. (2015). We performance within transformation at both firm and year dimension before estimation. The robust standard errors adjusted for firm-level clustering are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Dependent Variable: CAPX						
	(1)	(2)	(3)	(4)	(5)	(6)
CF	0.119***	0.125***	0.118***	0.127***	0.130***	0.124***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Q	0.005***	0.003***	0.006***	0.002***	0.001	0.003**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ICC-LNS	-0.037**					
	(0.02)					
ICC-GLS		-0.128***				
		(0.04)				
ICC-CT			-0.048**			
			(0.02)			
Eret-CAPM				0.102***		
				(0.02)		
Eret-FF3					0.117***	
					(0.02)	
Eret-FF4						0.032
						(0.03)
Year FE	No	No	No	No	No	No
Firm FE	No	No	No	No	No	No
Observations	38093	38180	37503	37176	37176	37176
rho	0.085	0.076	0.082	0.080	0.072	0.073

Table A.3: Controlling for Cummins et al. (2006)'s Real Q

This table provides estimation results from panel regression. The sample consists of US firms from 1985 to 2013. The dependent variable is capital expenditures (CAPX) scaled by beginning-of-year total assets (AT). ICC-LNS, ICC-GLS and ICC-CT are the implied cost of equity estimates following the methods of Li et al. (2013), Claus and Thomas (2001), and Gebhardt et al. (2001), respectively. Eret-CAPM, Eret-FF3, and Eret-FF4 are expected returns based on the CAPM, the FF3M, and the FF4M. All the cost-of-equity proxies are measured at the beginning of the year. Real Q is Cummins et al. (2006)'s q at the beginning of the year and CF is concurrent free cash flow. All regressions include year and firm fixed effects. Detailed definitions of variables are provided in Appendix B. The robust standard errors adjusted for firm-level clustering are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Dependent Variable: CAPX						
	(1)	(2)	(3)	(4)	(5)	(6)
CF	0.138***	0.137***	0.140***	0.144***	0.143***	0.143***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Real Q	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ICC-LNS	-0.059***					
	(0.01)					
ICC-GLS		-0.152***				
		(0.02)				
ICC-CT			-0.029***			
			(0.01)			
Eret-CAPM				0.043***		
				(0.01)		
Eret-FF3					0.018***	
					(0.01)	
Eret-FF4						0.020***
						(0.00)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	36009	35771	35359	33763	33763	33763
Adjusted R^2	0.151	0.151	0.148	0.151	0.150	0.150

Table A.4: The Performance of COE Proxies in Recession / Non-Recession Period

This table provides estimation results from panel regressions. The sample consists of US firms from 1985 to 2013. The dependent variable is capital expenditures (CAPX) scaled by beginning-of-year total assets (AT). ICC-LNS, ICC-GLS and ICC-CT are the implied cost of equity estimates following the methods of Li, Ng, and Swaminathan (2013), Claus and Thomas (2001), and Gebhardt, Lee, and Swaminathan (2001), respectively. Eret-CAPM, Eret-FF3, and Eret-FF4 are expected returns based on the CAPM, the FF3M, and the FF4M. All the cost-of-equity proxies are measured at the beginning of the year. Q is Tobin's q at the beginning of the year and CF is concurrent free cash flow. All regressions include year and firm fixed effects. Detailed definitions of variables are provided in Appendix B. The robust standard errors adjusted for firm-level clustering are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

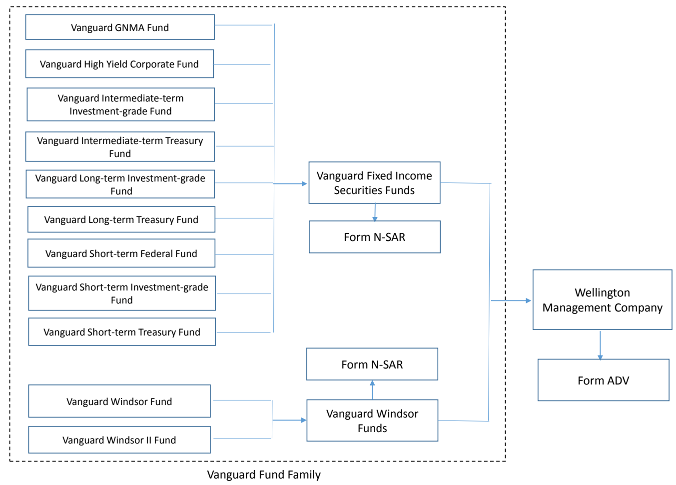
Panel A: Non-Recession Period						
	(1)	(2)	(3)	(4)	(5)	(6)
CF	0.112***	0.111***	0.108***	0.109***	0.108***	0.108***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Q	0.006***	0.006***	0.007***	0.006***	0.007***	0.006***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ICC-LNS	-0.039***					
	(0.01)					
ICC-GLS		-0.075***				
		(0.02)				
ICC-CT			-0.014*			
			(0.01)			
Eret-CAPM				0.030***		
				(0.01)		
Eret-FF3					0.007	
					(0.01)	
Eret-FF4						0.012***
						(0.00)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	31753	31803	31227	31019	31019	31019
Adjusted R^2	0.163	0.162	0.162	0.156	0.155	0.156
Panel B: Recession Period						
	(1)	(2)	(3)	(4)	(5)	(6)
CF	0.099***	0.100***	0.100***	0.103***	0.103***	0.102***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Q	0.007***	0.008***	0.008***	0.007***	0.007***	0.007***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ICC-LNS	-0.015					
	(0.02)					
ICC-GLS		0.022				
		(0.05)				
ICC-CT			-0.013			
			(0.02)			
Eret-CAPM				0.036**		
				(0.02)		
Eret-FF3					0.032***	
					(0.01)	
Eret-FF4						0.018
						(0.01)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	6340	6377	6276	6157	6157	6157
Adjusted R^2	0.201	0.201	0.202	0.191	0.192	0.191

Table A.5: Long-term Effects of the Cost-of-Equity Proxies

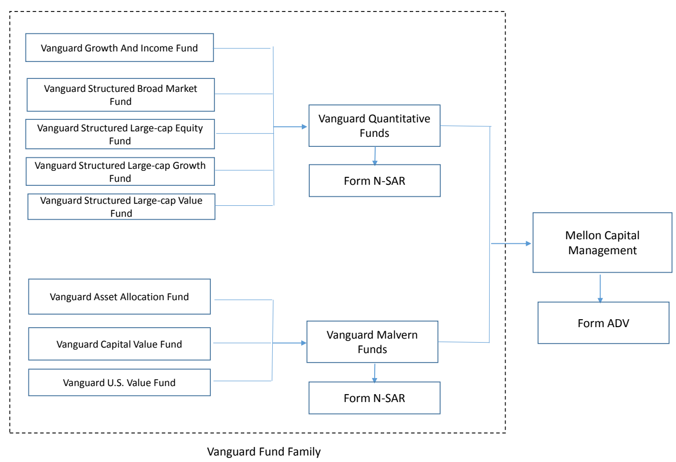
This table provides estimation results from panel regression. The sample consists of US firms from 1985 to 2013. The dependent variable is capital expenditures (CAPX) scaled by beginning-of-year total assets (AT). ICC-LNS, ICC-GLS and ICC-CT are the implied cost of equity estimates following the methods of Li et al. (2013), Claus and Thomas (2001), and Gebhardt et al. (2001), respectively. Eret-CAPM, Eret-FF3, and Eret-FF4 are expected returns based on the CAPM, the FF3M, and the FF4M. All the cost-of-equity proxies are measured at the year $t-1$ and $t-2$. Q is Tobin's q at the beginning of the year and CF is concurrent free cash flow. All regressions include year and firm fixed effects. Detailed definitions of variables are provided in Appendix B. The robust standard errors adjusted for firm-level clustering are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
CF	0.110***	0.105***	0.103***	0.105***	0.104***	0.104***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Q	0.006***	0.007***	0.007***	0.006***	0.006***	0.006***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$ICC-LNS_{t-1}$	-0.039***					
	(0.01)					
$ICC-LNS_{t-2}$	-0.000					
	(0.01)					
$ICC-GLS_{t-1}$		-0.078***				
		(0.02)				
$ICC-GLS_{t-2}$		-0.001				
		(0.02)				
$ICC-CT_{t-1}$			-0.013*			
			(0.01)			
$ICC-CT_{t-2}$			0.005			
			(0.01)			
$Eret-CAPM_{t-1}$				0.025***		
				(0.01)		
$Eret-CAPM_{t-2}$				0.011		
				(0.01)		
$Eret-FF3_{t-1}$					0.012**	
					(0.01)	
$Eret-FF3_{t-2}$					0.004	
					(0.00)	
$Eret-FF4_{t-1}$						0.007
						(0.00)
$Eret-FF4_{t-2}$						0.013***
						(0.00)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	36152	35563	34483	34516	34516	34516
Adjusted R^2	0.169	0.166	0.169	0.155	0.155	0.155

Chapter 2



(a) **Wellington Management Company**



(b) **Mellon Capital Management**

Figure A.1: An Example of Mutual Fund Advisor and Clients

This figure shows two examples of organization structure of mutual fund advisory business. Wellington Management Company and Mellon Capital Management are fund advisors who manage portfolios for mutual funds in the Vanguard fund family. The data is obtained from N-SAR filings in 2010.

Table A.6: Breakdown of Advisory Misconduct

This table reports the number and percentage of advisory misconduct with respect to product (Panel A), case initiator (Panel B), sanction (Panel C), resolution (Panel D), subject (Panel E) and allegation (Panel F), respectively. In Panel B-Panel F the sample is restricted to mutual fund advisory misconduct. The data is obtained from Regulatory Disclosure Reporting Page of Form ADV.

	Number	Percent
Panel A: Product		
OTC Equity	909	4.97
Listed Equity	1,111	6.08
Commodity Futures	252	1.38
Financial Futures	212	1.16
Insurance	1,530	8.37
Mutual Fund	1,033	5.65
Options	455	2.49
No Product	5,508	30.14
Others	7275	39.76
Total	18,276	100.00
Panel B: Case Initiator		
Foreign	64	6.20
Other	55	5.32
SEC	271	26.23
SRO	237	22.94
State	406	39.30
Total	1,033	100.00
Panel C: Sanction		
Cease and Desist	160	16.31
Censure	115	11.72
Civil/Admin. Penalties	460	46.89
Others	246	25.08
Total	981	100.00
Panel D: Resolution		
Acceptance, Waiver & Consent(AWC)	196	18.99
Consent	220	21.32
Order	166	16.09
Settled	248	24.03
Others	202	19.57
Total	1,032	100.00
Panel E: Subject		
Firm	455	45.91
Affiliates	452	45.61
Firm/Affiliates	84	8.48
Total	991	100.00
Panel F: Allegation		
Transaction	164	17.60
Disclosure	124	13.30
Compliance	644	69.10
Total	932	100.00

Table A.7: Examples of Mutual Fund Advisory Misconduct Cases

Advisor Name	Filing Date	Initiation Date	Initiator	Resolution Date	Alligation
ALLIANCE CAPITAL MANAGEMENT L.P.	2004/1/5	2003/8/25	State	2003/12/18	Market timing transactions of mutual fund shares, some of which had an adverse effect on mutual fund shareholders.
MFS INSTITUTIONAL ADVISORS INC.	2005/9/13	2004/2/5	SEC	2004/2/5	False and misleading information regarding market timing in certain mutual fund prospectuses for which Massachusetts Financial Services Company ("MFS") serves as investment adviser.
MILLENNIUM MANAGEMENT LLC.	2012/2/14	2005/12/1	SEC	2005/12/1	Certain deceptive practices related to mutual fund trading, including activities related to "market timing".
WACHOVIA SECURITIES, LLC.	2008/6/4	2007/9/19	SEC	2007/9/19	Entered into an agreement to allow a registered representative to market time in a specific evergreen fund in excess of trading limits set forth in the funds' prospectus.
MORGAN KEEGAN & COMPANY, INC.	2012/3/30	2010/4/5	State	2011/6/22	Engaged in fraudulent, dishonest or unethical business practices in violation of Alabama, Mississippi, South Carolina And Kentucky Securities Acts.
LINCOLN FINANCIAL SECURITIES CORPORATION	2008/12/3	2008/11/7	State	2008/11/7	Solicited and executed 4 mutual fund transactions between March 1, 2004 and April 30, 2004 while not being properly licensed in the state of New Hampshire.
CONCORD EQUITY GROUP ADVISORS, LLC.	2009/5/31	2007/8/13	State	2008/7/12	Put clients' accounts in investments with high commissions and excessive fees, and it failed to disclose such fees and charges, including contingent deferred sales charges.
THE HUNTINGTON INVESTMENT COMPANY	2005/8/19	2005/3/14	SRO	2005/6/30	Pay non-cash compensation for a sales contest, which weighted the member's products more than other investment products.
TEMENOS INC.	2007/3/15	2005/12/27	SRO	2006/5/10	Unauthorized trades and unauthorized disbursements.
HORNOR, TOWNSEND & KENT, INC.	2012/12/4	2012/10/2	SRO	2012/10/3	Failed to establish and maintain a supervisory system and establish, maintain and enforce written supervisory procedures.
MORGAN KEEGAN & COMPANY, INC.	2009/3/30	2007/6/4	State	2009/1/23	Fraudulent or deceptive practices in sale of securities.

Table A.8: Variable Definitions

Variable	Definitions
Netflow	Total NAV of shares sold less Total NAV of shares redeemed and repurchased (N-SAR Item 28), over total net assets (N-SAR Item 74-T).
Inflow	Total NAV of shares sold (N-SAR Item 28), over total net assets (N-SAR Item 74-T).
Outflow	Total NAV of shares redeemed and repurchased (N-SAR Item 28), over total net assets (N-SAR Item 74-T).
Return	$[NAV_t - NAV_{t-1}]/NAV_{t-1}$, where NAV is net asset value per share (N-SAR Item 74-V1)+Dividends from net investment income (N-SAR Item 73-A1)+distributions of capital gains(N-SAR Item 73-B1)+other distributions (N-SAR Item 73-C).
Monetary Fine	Total dollar amount of monetary fine associated with all misconduct.
Fund TNA	Total net assets of fund (N-SAR Item 74-T).
Fund Age	Number of years since inception in N-SAR filings database.
Expense Ratio	Total expenses (N-SAR Item 72-X) over total net assets (N-SAR Item 74-T), in percentage.
Front-End Load	Total front-end sales loads (N-SAR Item 30-A) over total net assets (N-SAR Item 74-T), in percentage.
Redemption Fee	Total deferred or contingent deferred sales loads (N-SAR Item 35) plus total amount of redemption fees other than deferred or contingent deferred sales loads (N-SAR Item 38), over total net assets (N-SAR Item 74-T), in percentage.
Fund Family TNA	Total net assets of funds within the same fund family, indicated by N-SAR Item 19-C.
Flow to Fund Style	Average netflow of funds belonging to the same investment style, where fund investment styles consist of equity (capital appreciation, growth and income, total return), bond, balanced, index, foreign and others.
Avg. Flow to Fund Style	Weighted average of *Flow to Fund Style* for an advisor, where the weight is calculated as percentage of TNA belonging to a particular style in total TNA managed by a advisor.
Total AUM	Total dollar amount of assets under management of an advisory firm (Form ADV Item 5F2).
Total Employees	Total number of employees of an advisory firm (Form ADV Item 5A).
Total Clients	Total number of clients of an advisory firm (Form ADV Item 5C1).
Total Accounts	Total number of client accounts of an advisory firm (Form ADV Item 5F2).
Firm Branches	Total number of an advisory firm's branches, including principal office (N-SAR Schedule D, Section 1.F).
Firm Age	Number of years since inception in Form ADV database.
Mutual Fund Misconduct Dummy	Dummy variable equals one if an advisor commits at least one mutual fund advisory misconduct in current period.
Regional Misconduct Intensity	Total number of existing mutual fund advisory misconduct scaled by population in a Zipcode region.
Interest in Transaction	Dummy variable equals one if at least one of the Items 8A1, 8A3, 8B2, 8B3 is ”Yes” in Form ADV.
Referral Fees	Dummy variable equals one if Item 8F is ”Yes” in Form ADV.
Soft Dollars	Dummy variable equals one if Item 8E is ”Yes” in Form ADV.
Broker in Firm	Dummy variable equals one if Item 5B2>0 in Form ADV.
Custody	Dummy variable equals one if at least one of the Items 9A1-2, 9B1-2 is ”Yes” in Form ADV.
Percent Client Agents	Percent of institutional clients, which is sum of ADV Item 5D1-C, 5D1-D, 5D1-H, 5D1-I, 5D1-J.

Chapter 3

Table A.9: Variable Definitions

Variable	Definitions
Fund Return	Weekly fund returns calculated from TNA-weighted CRSP fund-share class returns.
Fund TNA	Total net assets of fund (N-SAR Item 74-T).
Expense Ratio	Total expenses (N-SAR Item 72-X) over total net assets (N-SAR Item 74-T), in percentage.
Front-End Load	Total front-end sales loads (N-SAR Item 30-A) over total net assets (N-SAR Item 74-T), in percentage.
Redemption Fee	Total deferred or contingent deferred sales loads (N-SAR Item 35) plus total amount of redemption fees other than deferred or contingent deferred sales loads (N-SAR Item 38), over total net assets (N-SAR Item 74-T), in percentage.
ILP	A dummy variable equals one if the fund family is eligible for lending facility through Interfund Lending Programs in month t, and zero otherwise.
Distress (Bottom 3%)	A dummy variable equals one if the funds with investment style i has average returns in week t below bottom 3rd percentile of all weekly returns in the whole sample, and zero otherwise.
Distress (Bottom 2%)	A dummy variable equals one if the funds with investment style i has average returns in week t below bottom 2nd percentile of all weekly returns in the whole sample, and zero otherwise.
Distress (Bottom 1%)	A dummy variable equals one if the funds with investment style i has average returns in week t below bottom 1th percentile of all weekly returns in the whole sample, and zero otherwise.
Distress (Bottom 0.5%)	A dummy variable equals one if the funds with investment style i has average returns in week t below bottom 0.5th percentile of all weekly returns in the whole sample, and zero otherwise.
Distress (Bottom 0.25%)	A dummy variable equals one if the funds with investment style i has average returns in week t below bottom 0.25th percentile of all weekly returns in the whole sample, and zero otherwise.
Intra-Family Style Diversity	Herfindahl-Hirschman Index (HHI) of fund total net assets, where the HHI is calculated as summation of squared proportion of TNA belonging to the CRSP 4-digit style codes within family.
External Borrowing	A dummy variable equals one if the funds have any amount of bank overdraft (N-SAR Item 55-A) / bank loan (N-SAR Item 55-B), or engaged in borrowing activities ((N-SAR Item 77-O) in year t.

Table A.10: Interfund Lending Program: Application and Order Date

N-SAR Family Name	Application Date	SEC Order Date
STEINROEMF	25-Jul-95	
VANGUARDGR	22-Sep-95	
JANUSCAPIT	9-Dec-96	
TROWEPRICE	30-Sep-98	
FIDELITYZZ	27-Feb-98	
FRNKTEMGRP	5-Feb-99	
FEDERATEDX	29-Jul-99	
AMERICENIN	25-Oct-99	
INVESCOFDS	13-Nov-98	
SCUDDERRRR	16-Jul-99	
EVERGREENS	22-Apr-99	
SCHWABFUND	17-May-00	
PUTNAMFUND	6-Oct-97	
FIRSTAMERI	28-Sep-01	
ONEGROUPTR	23-Mar-01	
EATONVANCE	18-Feb-00	
OPPENHEIMR	14-Nov-01	
PBHGADVISO	16-Apr-02	
NATIONSFUN	26-Feb-02	
AMERAADVFD	19-Mar-02	
DREYFUSFAM	1-Mar-01	
SEILIQUIDA	16-May-02	
SEIFINSVCO	16-May-02	
SEIASSETAL	16-May-02	
SEIINSPROD	16-May-02	
SEIOPPMAST	16-May-02	
SEIALPHALP	16-May-02	
IXISLOOMIS	12-Dec-02	
THRIVENTMF	11-Dec-03	
RLINSFUNDS	19-Jul-05	
WELLSFARGO	14-May-03	
RIVERSORCE	26-Mar-02	
COLUMBIAFD	26-Mar-02	
PIONEERFDS	24-Sep-07	4-Mar-08
DODGECXFDS	18-Jan-08	27-Oct-08
MNGRSTRSTI	24-Jul-08	23-Jun-09
MANAGERSFD	24-Jul-08	23-Jun-09
ALGERFUNDS	25-Sep-08	11-Aug-09
NORTHTRUST	30-Sep-09	18-Aug-10
PRINCORGRP	16-Feb-11	25-Oct-11
MASSFINSER	20-Nov-08	26-Oct-11
JOHNHANCOC	31-Dec-08	14-Dec-11
DFA INVEST	5-Sep-13	2-Apr-14
UNITDGROUP	25-Sep-13	30-Jun-14
IVYFAMILY1	25-Sep-13	30-Jun-14
JACKSONNAT	24-Jan-14	20-Oct-14
JNLVARFND1	25-Jan-14	21-Oct-14
JNLNYVARII	26-Jan-14	22-Oct-14
JNLVARIABL	27-Jan-14	23-Oct-14
FIRSTTRUST	28-Jan-14	24-Oct-14
JNLINVESTR	29-Jan-14	25-Oct-14
CRMCFNDGRP	30-Oct-14	19-Apr-16
TCWFUNDINC	5-Oct-15	7-Jun-16
TCW/WITTER	6-Oct-15	8-Jun-16
TCW/DEANWI	7-Oct-15	9-Jun-16
TCW/DWXXXX	8-Oct-15	10-Jun-16
NATIONWIDE	29-Oct-15	13-Jun-16

Table A.11: Description of Fund Investment Styles

CRSP Style Code	Style Name
EDCI	Equity-Domestic: Cap Based: Micro
EDCL	Equity-Domestic: Cap Based: Large
EDCM	Equity-Domestic: Cap Based: Mid
EDCS	Equity-Domestic: Cap Based: Small
EDSA	Equity-Domestic: Sector: Telecom
EDSC	Equity-Domestic: Sector: Commodities
EDSF	Equity-Domestic: Sector: Financial
EDSG	Equity-Domestic: Sector: Gold
EDSH	Equity-Domestic: Sector: Health
EDSI	Equity-Domestic: Sector: Industrials
EDSM	Equity-Domestic: Sector: Materials
EDSN	Equity-Domestic: Sector: Natural Resources
EDSR	Equity-Domestic: Sector: Real Estate
EDSS	Equity-Domestic: Sector: Consumer Services
EDST	Equity-Domestic: Sector: Technology
EDSU	Equity-Domestic: Sector: Utilities
EDYB	Equity-Domestic: Style: Growth & Income
EDYG	Equity-Domestic: Style: Growth
EDYH	Equity-Domestic: Style: Hedged
EDYI	Equity-Domestic: Style: Income
EDYS	Equity-Domestic: Style: Short
EF	Equity-Foreign: General
EFCS	Equity-Foreign: Cap Based: Small
EFRC	Equity-Foreign: Regional: Canada
EFRE	Equity-Foreign: Regional: European
EFRI	Equity-Foreign: Regional: India
EFRJ	Equity-Foreign: Regional: Japan
EFRL	Equity-Foreign: Regional: Latin America
EFRM	Equity-Foreign: Regional: Emerging Markets
EFRP	Equity-Foreign: Regional: Pacific
EFRQ	Equity-Foreign: Regional: China
EFRX	Equity-Foreign: Regional: Pacific Ex Japan
EFSF	Equity-Foreign: Sector: Financial
EFSH	Equity-Foreign: Sector: Health
EFSI	Equity-Foreign: Sector: Industrials
EFSN	Equity-Foreign: Sector: Natural Resources
EFSR	Equity-Foreign: Sector: Real Estate
EFST	Equity-Foreign: Sector: Technology
EFYG	Equity-Foreign: Style: Growth
EFYT	Equity-Foreign: Style: Total Return
I	Fixed Income: General
IC	Fixed Income: Corporate
ICQH	Fixed Income: Corporate: Quality: High
ICQY	Fixed Income: Corporate: Quality: High Yield
IF	Fixed Income: Foreign: General
IFM	Fixed Income: Foreign: Money Market
IG	Fixed Income: Government: General
IGD	Fixed Income: Government: Duration
IGDI	Fixed Income: Government: Duration: Intermediate
IGDS	Fixed Income: Government: Duration: Short
IGT	Fixed Income: Government: TIPS
IM	Fixed Income: Money Market: General
IMM	Fixed Income: Money Market: Muni
IU	Fixed Income: Municipal: General
IUI	Fixed Income: Municipal: Intermediate
IUS	Fixed Income: Municipal: Short
M	Balanced: General
MT	Balanced: Target Date
O	Others: General
OC	Others: Currency
OM	Others: Mortgage-backed

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